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COMPUTER-BASED IMPULSIVE PROCESS INTERVENTIONS IN DIETARY BEHAVIOR

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DOCTORAL DISSERTATION

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ABSTRACT

Unhealthy foods are often appetizing and thus hard to resist, despite knowledge about their detrimental effects on health. The psychological processes underlying choices between immediately rewarding but health-harming and potentially less rewarding but health-promoting options have been described in dual-process models such as the Reflective-Impulsive Model.

These models assume two interacting kinds of processes: one impulsive, association-based, fast, and effortless; the other reflective, based on syllogistic reasoning, slow, and dependent on cognitive resources. While most interventions on eating behavior aim to alter reflective reasoning and increase its influence on behavior, some relatively new computer-based interventions aim to directly change impulsive aspects of food intake. They do so by presenting users images of unhealthy food while asking them to show a behavior that is inconsistent with their impulse to approach, i.e. inhibit a response or show an avoidance reaction. This way, the association between unhealthy foods and approach behavior is broken up, reducing the strength of elicited impulses in the future. Evidence has mounted that particularly the Go/No-Go task can reduce intake of unhealthy foods. In this task, participants need to inhibit their impulse to react when seeing unhealthy food images, creating an "unhealthy-stop" association.

Two important questions have remained unanswered in this research line: (1) What are the psychological mechanisms of behavioral effects in these interventions? (2) How well do laboratory-based demonstrations of efficacy translate to real-world behavior change? This thesis aims to produce evidence that helps answer those questions and enhance understanding of impulsive process interventions by (1) meta-analyzing the scientific literature with a specific focus on implicit bias change as a potential psychological mechanism (Study I), (2) examining a potential neural marker of the psychological mechanisms involved (Study II), and (3) investigating relevant aspects of such an intervention in the field (Study III). Study I thereby lays the foundation for the main research questions and study design in Studies II and III.

The specific aims of Study I were to provide an overview of the literature on different kinds of computer-based impulsive process interventions by meta-analyzing their effects on eating behavior. In addition, it aimed to identify study-level moderators of effects, to investigate implicit bias change in the included studies as a potential mechanism of behavioral effects, and thus to identify ways forward for the research area. Study II followed up on the results of Study I and aimed to identify the role of a neural marker of the involved psychological processes, the N2 event-related potential (ERP), by measuring neural activity during the performance of an impulsive process intervention. Study III then used data from a field trial to investigate dose-

response relationships in an impulsive process intervention in order to provide best-practice guidance for future intervention users.

The studies in this thesis used a range of methods to answer the specific research questions. In Study I, I conducted a systematic literature review with meta-analysis. Meta-regressions with categorical and continuous predictors tested potential moderating variables and the relationship between behavioral effects and a hypothesized psychological mechanism of effects. In Study II, a specific neural marker, the N2 ERP , was analyzed during food Go/No-Go training and related to food intake both within and outside the laboratory. Study III used data from a pragmatic open trial in which participants used smartphone-based Go/No-Go training at their own discretion to determine dose-response relationships for intake of different food categories.

Study I identified 30 randomized controlled trials with 47 effect sizes, delivering at least one of four computer-based impulsive process interventions, for inclusion in the analyses. The overall effect size for eating behavior was small ($g = -0.17$, $CI95 = [-0.29; -0.05]$, $p = .01$) with only the Go/No-Go task showing significant effects ($g = -0.39$, $CI95= [-0.57; -0.22]$, $p < .001$). The effects on implicit biases were also significantly different from zero ($g = -0.46$, $CI95= [-0.68; -0.25]$, $p < .001$) and the effects on bias change and eating behavior were significantly related ($B = .42$, $CI95= [.02; .81]$, $z = 2.07$, $p = .04$, $k = 21$). Against preregistered hypotheses, analyses in Study II showed no significant differences between healthy and unhealthy foods in N2 ERP strength ($p = .18$, $\eta p2 = 0.04$), no effect of Go/No-Go training on immediate food intake ($p = .50$) or N2 amplitudes ($p = .57$, $\eta p2 = 0.0004$), and no relationship between N2 and food intake both inside ($B = -0.41$, $p = .82$) and outside ($B = 166.21$, $p = .53$) the laboratory. In Study 3, analyses revealed significant relationships between the self-administered amount of conducted Go/No-Go training and self-reported food intake, such that conducting more blocks of training led to decreased unhealthy ($\beta = -0.004$, $CI95 = [-0.006; -0.002]$) and increased healthy food intake ($b = 0.003$, $CI95 = [0; 0.005]$). Separate analyses for different food types indicated variations between food categories in their dose-response relationship, indicating that completing about 8 to 24 4-minute sessions of Go/No-Go training over the course of one month leads to changes in intake by one point.

The scientific contribution of this work is thus threefold. Firstly, it provides an overview of the research field, providing a clear recommendation for the precise task to use for intervention delivery, and indicates future directions for the field (Study I). Secondly, it contributes to the ongoing debate about psychological and neural mechanisms of impulsive process interventions in eating behavior and indicates changes in impulsive processes to be one driver of behavioral effects (Studies I and II). Lastly, it provides estimates for necessary dosage and usage recommendations based on real-world data from smartphone-delivered training (Study III), a promising future avenue for large-scale, self-administered training.

Based on this thesis, future research should aim to further clarify psychological training mechanisms, establish ideal training design and training schedules, identify groups for whom training is most beneficial, and seek synergistic effects with other interventions targeting eating behavior.

TIIVISTELMÄ

Epäterveelliset ruoat ovat usein houkuttelevia ja siten vaikeita vastustaa huolimatta niiden vahingollisista vaikutuksista terveydelle. Kaksoisprosessointimallit, kuten reflektiivis-impulsiivinen malli kuvaa psykologisia prosesseja, jotka vaikuttavat välittömästi palkitsevien mutta terveyttä vahingoittavien ja vähemmän palkitsevien mutta terveyttä edistävien valintojen takana. Nämä mallit pitävät sisällään kaksi vuorovaikuttavaa prosessia, joista toinen on impulsiivinen, nopea prosessi ja toinen reflektiivinen, hidas ja kognitiivisista resursseista riippuvainen prosessi.

Useimmat syömiskäyttäytymiseen kohdistuvat interventiot pyrkivät muovaamaan reflektiivisiä prosesseja ja vaikuttamaan niiden kautta käyttäytymiseen. Uudemmat digitaaliset interventiot pyrkivät kuitenkin muuttamaan suoraan syömisen impulsiivisia aspekteja. Tällaiset interventiot ovat pelinomaisia tietokonetehtäviä, joissa käyttäjille esitetään kuvia epäterveellisistä ruoista (kuten suklaa), joihin ei tehtävän kuluessa saa reagoida tai joihin on reagoitava impulssin vastaisesti. Tehtävän tavoitteena on siten vähentää epäterveellisen ruoan ja siihen reagoivan käyttäytymisen assosiaatiota. Tämän väitöskirjatutkimuksen tarkoituksena oli parantaa ymmärrystä näistä impulsiivisiin prosesseihin kohdistetuista interventioista.

Tutkimus koostui kolmesta osatutkimuksesta. Ensimmäinen osatutkimus oli erilaisia digitaalisia ja syömiskäyttäytymisen impulsiivisiin prosesseihin kohdistettuja interventiotutkimuksia koskeva meta-analyysi. Sen tarkoituksena oli selvittää mitkä interventiot ovat vaikuttavimpia, sekä sitä missä olosuhteissa kyseiset interventiot vaikuttavat käyttäytymiseen eniten ja mikä on käyttäytymisen taustalla vaikuttava psykologinen mekanismi. Toisen osatutkimuksen tavoitteena oli tunnistaa syömiskäyttäytymisen impulsiivisiin prosesseihin liittyviä neuraalisen aktivaation piirteitä mittaamalla aivosähkökäyrällä osallistujien N2 herätevasteita syömisimpulsseihin kohdistetun intervention aikana. Kolmannessa osatutkimuksessa käytettiin mobiilisovellusta ja tutkittiin kenttätutkimuksesta saadun tiedon avulla altistus-vaste-suhteita syömisimpulsseihin kohdistetuissa interventioissa.

Ensimmäisessä osatutkimuksessa systemaattinen kirjallisuuskatsaus tunnisti 30 artikkelia. Interventioilla oli pieni, mutta merkittävä vaikutus syömiskäyttäytymiseen ($g = -0.17$, $CI95 = [-0.29; -0.05]$, $p = .01$). Vain niin sanotun Go/No-Go impulssin kontrollitehtävän havaittiin vaikuttavan syömiskäyttäytymiseen ($g = -0.39$, $CI95 = [-0.57; -0.22]$, $p < .001$). Myös toisessa osatutkimuksessa impulsiivisen reaktion hillintään liittyvät N2 herätevasteet olivat hypoteesin vastaisesti riippumattomia esitettyjen ruokakuvien kaloripitoisuudesta ($p = .18$, $\eta p2 = 0.04$) eikä niiden vahvuudessa vastoin odotuksia havaittu muutosta intervention kuluessa ($p = .57$, $\eta p2 =$

0.0004). Lisäksi herätevasteen voimakkuudella ei havaittu olevan yhteyttä kalorikulutukseen intervention aikana ($B = -0.41$, $p = .82$) tai sen jälkeen ($B = 166.21$, $p = .53$). Kolmannessa osatutkimuksessa havaittiin, että mitä enemmän osallistuja käytti sovellusta, sitä suurempi oli sen vaikutus käyttäytymiseen; epäterveellisen ruoan syöminen väheni ($\beta = -0.004$, $CI95 = [-0.006; -0.002]$), kun taas terveellisen ruoan syöminen lisääntyi ($b = 0.003$, $CI95 = [0; 0.005]$).

Väitöskirjatutkimuksen tieteellinen kontribuutio voidaan tiivistää kolmeen päälöydökseen. Ensinnäkin, meta-analyysi tähänastisista tutkimuksista osoitti, että No-Go/Go impulssikontrollitehtävällä oli selkein vaikutus syömiskäyttäytymiseen ja impulssikontrolliin. Tulevissa interventioissa tämä on lupaavin tehtävä. Toiseksi, väitöskirjan aivovasteisiin liittyvällä osatutkimuksella on suuri merkitys impulsiivisiinprosesseihin kohdistuvien interventioiden psykologisten mekanismien ymmärtämiselle. Tulokset kyseenalaistavat aikaisemman käsityksen, että impulssikontrolliresurssien vahvistuminen selittäisi intervention vaikutusta syömiseen. Tämän sijaan tulokset osatutkimuksesta 1 ja 2 tukevat vaihtoehtoista tulkintaa, jonka mukaan muutokset ruokien impulsiivisissa prosesseissa selittävät intervention vaikutuksia syömiskäyttäytymiseen. Kolmantena päälöydöksenä ovat kenttäkokeessa saadut havainnot tarvittavasta annosmäärästä ja käyttötavasta mobiililaitteella toteutetuissa interventioissa, jotka tarjoavat lupaavan pohjan itseohjattuun syömiskäyttäytymisen muutokseen.

Tulevan tutkimuksen tulisi selventää interventioiden psykologisia mekanismeja, tuottaa tarkoituksenmukaisia ohjeita sovellusten käyttäjille ja identifioida ryhmiä, jotka hyötyvät interventioista eniten. Tämän ohella tutkimuksen tulisi jatkossa etsiä syömiskäyttäytymiseen kohdistuvien interventioiden synergistisiä vaikutuksia.

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CONTENTS

LIST OF ORIGINAL PUBLICATIONS

This thesis is based on the following publications:

I Aulbach, M. B., Knittle, K., & Haukkala, A. (2019). Implicit process interventions in eating behaviour: A meta-analysis examining mediators and moderators. Health Psychology Review, 13(2), 179–208. https://doi.org/10.1080/17437199.2019.1571933

II Aulbach, M. B., Harjunen, V. J., Spapé, M., Knittle, K., Haukkala, A., & Ravaja, N. (2020). No evidence of calorie-related modulation of N2 in food-related Go/No-Go training: A preregistered ERP study. Psychophysiology, 57(4), e13518. https://doi.org/10.1111/psyp.13518

III Aulbach, M. B., Knittle, K., van Beurden, S., Haukkala, A., & Lawrence, N. (under review). Is more better and how much is enough? Dose-response relationships in app-based food Go/No-Go training. Retrieved from psyarxiv.com/nqax3. Doi: 10.31234/osf.io/nqax3

The publications are referred to in the text by their roman numerals.

ABBREVIATIONS

BMI	Body mass index
BSI	Behavior-Stimulus Interaction
EMA	Ecological momentary assessment
ERP	Event-related potential
IAT	Implicit association test
RCT	Randomised controlled trial
RIM	Reflective-Impulsive Model

1 INTRODUCTION

Food is generally desirable and unhealthy foods (i.e. those high in sugar, saturated fat, and/or salt) seem to be even more so than their healthy counterparts (Raghunathan et al., 2006). While this might seem like a sad fact of life for many it need not be for everyone (van der Heijden et al., 2020; Werle et al., 2013) and I will review evidence that demonstrates how these perceptions can change through behavioral interventions (Chen et al., 2019), which are at the core of this thesis.

The appealing nature of unhealthy food is not without consequences: an estimated 39% of adults worldwide (and even more in industrialized countries) are considered overweight by the World Health Organization, mostly caused by an imbalance between energy intake and expenditure (Global Health Observatory, 2017). This contributes to increases in the prevalence of diabetes, cardiovascular disease, and certain cancers (World Health Organization, 2018) as well as mental health issues (Centers for Disease Control and Prevention, 2020) with massive costs in terms of individual human suffering and economic damage to healthcare systems (World Health Organization, 2015). Assuming that most people want to live a long and healthy life and therefore try to restrict their food intake (Santos et al., 2017), this leaves the conclusion that many people act against their long-term goals and instead follow impulses for instant reward through food, a phenomenon commonly called “intention-behavior gap” (Sheeran & Webb, 2016).

A major contributor to the problem of overweight on a societal level is the over-consumption of energy-dense foods provided by the obesogenic environment many people live in. Food of low quality and poor nutritional value is always available at low financial cost and high convenience (Darmon & Drewnowski, 2015). This constant exposure to appealing, calorie-dense food activates reward systems in our brains (Mengotti et al., 2019) and can trigger behavioral impulses to obtain and consume those foods despite opposing longer-term goals. Consequences include both the selection of more energy-dense alternatives and overconsumption of such foods.

This problem is intensified by the fact that much of human behavior is habitual, in the sense that it is largely independent of long-term goals and executed in a rather automatic fashion without giving it much thought (Ouellette & Wood, 1998). Once unhealthy eating has become automatic and habitual, it is unlikely to change without intervention (van’t Riet et al., 2011).

Interventions aiming to support weight loss or maintenance through dietary change often work on the premise that people are able and willing to voluntarily override their short-term desires for unhealthy foods and choose healthier options that might seem less desirable to them. Interventions following this logic include assisting participants to set goals (Pearson, 2012) or self-monitor their weight or behavior (Burke et al., 2011; Michie et al., 2009) and show some degree of success but with much room for improvement (Wilfley et al., 2018), especially in terms of maintaining weight loss or target behavior (Christiansen et al., 2007; Dombrowski et al., 2014). However, their inherent logic is to help participants overcome their innate desire for unhealthy foods.

This thesis will review and provide evidence for the effectiveness of a line of intervention research that seeks a different approach to the problem: not to override dysfunctional impulses through self-control or willpower but to reduce the impulse to indulge in unhealthy eating to begin with and thus align the short-term goal to consume liked foods with the long-term goal to stay healthy. The thesis gives a meta-analytical overview of the effectiveness of different such computer-based interventions that make unhealthy foods less desirable and aims to contribute to theoretical debates about psychological mechanisms of behavior change. In addition, it provides practically useful guidance on possible future mobile-based intervention delivery.

2 THEORETICAL BACKGROUND

Several theoretical frameworks aim to explain the psychological processes involved in the trade-off between short-term desires and long-term goals, potentially starting with one of the founding fathers of social psychology, Kurt Lewin (1935) who would describe this as an approach-avoidance conflict. One of the most global modern theories is the Reflective-Impulsive Model (RIM) by Strack and Deutsch (2004) but other, more specific, theories have been proposed to explain dietary behavior in the face of food temptations. Specifically, I will give an overview of the Goal Conflict Model of Eating Behavior (Stroebe et al., 2013) and Behavior-Stimulus Interaction theory (Veling et al., 2008) and attempt to integrate them with the Reflective-Impulsive Model. I will not attempt to review which of the theories are a more accurate description of the world but rather provide the theoretical basis for the research presented in this thesis and allow for an understanding of this research from different theoretical angles. For the sake of clarity and brevity, I focus on these theories and exclude other theoretical accounts such as Incentive-Sensitization Theory, which originated in the addiction domain (Berridge, 2009; Berridge & Robinson, 2016). I also refrain from discussion of Restraint Theory (Herman & Mack, 1975) or the Boundary Model of Eating (Herman & Polivy, 1983), which were amongst the first theories to account for cognitive factors in eating behavior. Their focus on the role of dietary restraint laid the foundation for the Goal Conflict Model (Stroebe et al., 2013).

2.1 THE REFLECTIVE-IMPULSIVE MODEL

The Reflective-Impulsive Model (Strack & Deutsch, 2004) draws on the ancient idea that different parts or aspects of a person contribute to behavior and is thus considered a dual-process model. It specifies how impulsive and reflective psychological processes jointly guide human behavior and outlines guiding principles for the two different systems. In brief, it postulates that the reflective system works slowly and with cognitive effort while the impulsive system works fast and with minimal effort. The model outlines how the systems constantly interact in guiding behavior and under which conditions the respective systems are most likely to affect behavior.

Exemplifying the respective roles of the systems in the context of eating behavior, the reflective system best handles conscious goals and factual knowledge, such as a goal to keep a healthy diet and facts about nutritional content of different foods. This kind of knowledge can be acquired by single instance learning or retrieved from long-term memory and is then processed through syllogistic reasoning, features that make the reflective system very flexible. For example, Herb, a customer at a fast food joint might encounter a hamburger, retrieve from memory the fact that fast food is unhealthy, apply this general knowledge about hamburgers to the specimen at hand, and infer that this particular hamburger is, indeed, detrimental to his health. At the same time, Herb might have a goal to keep a healthy diet and if this goal is also retrieved, the reflective system's strive for consistency will lead to a behavioral decision and ultimately the activation of a motor schema that guides him away from the burger.

The impulsive system, on the other hand, is not based on propositional categorizations, but on associative networks. Stimuli are represented as nodes in a network that are connected by associative links of differing strength. The strength of the links depends on the frequency and recency of their activation so that the network represents co-occurrence of stimuli (Gawronski & Bodenhausen, 2006). Links can also be built through repeated reflective operations such as when the same contents are co-activated repeatedly (Smith & DeCoster, 2000). When one node gets activated through internal or external cues activation spreads through the network according to the strength of the links so nearby nodes are activated as well. Due to the network structure, cues that commonly co-occur can activate each other, such as when a television set can activate cravings for chips because one often eats chips while watching one's favorite TV show.

The activation of a network around an attractive food item can lead to the activation of behavioral schemata: "associative clusters [that] will emerge in the impulsive system that bind together frequently co-occurring motor representations with their conditions and their consequences" (Strack & Deutsch, 2004, p. 229). These can then be executed without a behavioral decision or conscious intention to do so. Crucially, the associative links between nodes are bi-directional so the activation (and execution) of motor schemata can, in turn, feed back to the nodes they are connected to (Neumann et al., 2003). Going back to our example, the perception of a hamburger and its smell triggers activation of nodes that have often been associated with concepts such as "tasty", which in turn activates behavioral schemata to approach the food and consume it. This strengthens the already existing links between burgers, the concept "tasty" and the behavioral schema.

In our exemplary fast food customer, the behavioral schemata activated by the reflective and the impulsive system are in contrast, a situation that is familiar to many. Given that the reflective system is slow and effortful and requires cognitive resources, Herb's actions depend on his motivation and capacity to engage the reflective system. This depends on things like his general working memory capacity (Hofmann, Gschwendner, et al., 2008) or whether he has consumed alcohol (Hofmann & Friese, 2008). If motivation and ability are high (Herb is wide awake and highly motivated to engage in reasoning), the reflective system can override the outcome of the impulsive system and initiate behavior that is in line with the activated goal of eating healthily. In case cognitive resources are low, he will most likely enact the behavioral schemata activated by the impulsive system and indulge in the burger. Importantly, the two systems interact in other ways: one crucial way how this happens is when activated contents from the associative store are activated and used in reflective reasoning. For example, a target stimulus can automatically activate positive associations, giving rise to a positive "gut feeling" about the target. While the person might not be aware of how and why this positive feeling came about, she is aware of the positive feeling and might use it as an argument in the reflective decision-making process and, for example, purchase the item that was associated with this positive feeling.

An important concept that can be framed in terms of the RIM is that of habit, commonly understood as behavior based on associations between a context and a behavior which is elicited automatically by those contexts (Verplanken & Aarts, 1999). It is obvious from this definition that habits function in line with the principles of the impulsive system of the RIM: the context automatically triggers behavior without goal-related deliberation because context and behavior have been tied together by mere association (Strack & Deutsch, 2004).

2.2 THE GOAL CONFLICT MODEL OF EATING BEHAVIOR

The phenomenon that some people diet successfully while others fail to lose or maintain weight is at the core of the Goal Conflict Model of Eating Behavior (Stroebe et al., 2013). It postulates that people who attempt to control their food intake ("restrained eaters") have two food-related goals that are in contrast to each other: on the one hand they have a dieting goal that can be linked to other, higher-order goals such as remaining healthy or adhering to certain physical beauty standards. On the other hand, they also have a hedonic goal of enjoying foods they like. Eating behavior is determined by the relative strength and accessibility of the respective goals. Once either of the goals is activated by internal or external cues, the other goal is inhibited. The hamburger in the fast-food joint activates Herb's enjoyment goal, which in turn "tunes down" the weight control goal he might hold. In turn, this leads to behavior in line with the enjoyment goal. If, however, the customer encounters a cue that activates his dieting goal (such as an advertisement for diet options, Papies & Veling, 2013) behavior would more likely be guided by that dieting goal.

The Goal Conflict Model incorporates the fact that a substantial share of dieters are successful by allowing the possibility that the very cues that trigger the eating enjoyment goal can also activate weight control goals (Fishbach et al., 2003), which in turn down-regulate the eating enjoyment goal. This happens when someone manages to repeatedly resist the temptation presented by unhealthy food cues and thus learns to associate hedonic cues with the weight control goal. This way, the temptation becomes its own "antidote". Notably, the authors emphasize that these processes can but need not happen with conscious awareness.

The authors of the Goal Conflict Model mention two fundamental differences between their model and dual-process models such as the RIM. First, the RIM postulates two separate memory systems which reflective and impulsive processes rely upon whereas the Goal Conflict Model does not make that assumption. Second, while goals are the core concept of the Goal Conflict Model, they are not central to the RIM (Stroebe et al., 2013). In brief, the main difference thus is that the Goal Conflict Model assumes the involved processes to be of the same nature: eating behavior is always related to a goal whereas the RIM postulates two qualitatively different kinds of processes that interact to determine behavior.

2.3 BEHAVIOR-STIMULUS INTERACTION THEORY

Behavior-Stimulus Interaction (BSI) Theory (Veling et al., 2008) can be regarded as a micro-theory that specifies certain aspects of the RIM, aiming to explain how behavior is regulated when behavioral impulses run counter situational demands.

BSI theory starts from the assumption that encountering a positive stimulus triggers a behavioral approach tendency and that this tendency can be inappropriate to act upon in certain situations (Herb sees a burger he wants to eat but has not paid for it yet). This conflict is detected and the impulse inhibited. This inhibition in itself, however, does nothing to alter the conflicting nature of the situation and would leave the person in a paralyzed state in which neither approach nor avoidance tendencies would "win over" the other to determine behavior. BSI therefore states that the experienced conflict triggers negative affect (as predicted by the affective-signaling hypothesis, Dignath et al., 2020), that this negative affect is attached to the encountered stimulus, and the stimulus is devalued in order to resolve the conflict: it simply becomes less alluring to engage in the impulsive behavior. Since the conflict between the impulse to approach and the requirement to inhibit is a central piece of the process, only initially alluring stimuli will be devalued. Stimuli that are initially neutral or negative do not trigger the approach tendency and thus no conflict is experienced.

BSI theory follows the RIM as it predicts a feedback from behavior (inhibiting a response) to the evaluation of the stimulus, a prediction that runs counter to the intuitive logic of evaluations driving behavior. Since the behavior is crucial in this circuit, this goes beyond mere effects of evaluative conditioning where appetitive stimuli are observed in close temporal proximity with unpleasant stimuli (see section Evaluative conditioning below, Chen et al., 2016).

2.4 INTEGRATING THE THREE MODELS

What to make of these three accounts that make different assumptions about the workings of the human mind? For the purposes of the work presented in this thesis, their commonalities are larger than their discrepancies and can thus be integrated and used as somewhat different ways to understand the presented research.

While the RIM is typically presented with two pathways that presumably only allow one concept to be "activated" in each system, it does not forbid activation of several contents at the same time. Here lies the connection to the Goal Conflict Model: encountering tasty yet unhealthy food activates both a hedonic and a dieting goal and "loads" them from the associative store to the reflective system where they can be subjected to propositional reasoning. However, this only happens if the associative network around those food cues does include the dieting goal. This, in turn, depends on the strength of the goal, how closely it is connected to the food cue, and on the context in which the cue is encountered. If the dieting goal is not activated, there is no conflict and the hedonic goal is acted upon. If the dieting goal is activated and its association with the behavioral schema to avoid the food is stronger than the association of the hedonic goal with the behavioral schema to approach, then the food is avoided. An important contribution of the Goal Conflict Model is that unhealthy food choices need not be impulsive: they can be the result of "rational" propositional reasoning when the enjoyment goal is valued more than the dieting goal, something that seems to be overlooked in much health-behavior research (De Witt Huberts et al., 2014; van Koningsbruggen et al., 2013).

BSI theory comes into play in situations where people resist temptations due to situational constraints and not due to propositional reasoning. When this happens, the negative affect associated with the behavioral conflict is attached to the encountered stimulus and it is thus devaluated. In terms of the RIM, this would lead to a change of the associative network underlying the impulsive system as it does not rely on propositional reasoning in the reflective system. Instead, it relies on the bi-directionality of the link between behavior and evaluations in that it is the behavior (i.e. not acting on a stimulus) that feeds back on the evaluation of the stimulus.

2.5 "IMPLICIT" PROCESSES

The literature around dual-process models such as the RIM is full of conceptual and terminological confusion (e.g. Corneille & Hütter, 2020; Keren & Schul, 2009). In particular, the term "implicit" has been debated thoroughly and therefore warrants clarification. "Implicit cognition" has been defined, amongst other definitions, as follows:

> *A template for definitions of specific categories of implicit cognition is: An implicit **C** is the introspectively unidentified (or inaccurately identified) trace of past experience that mediates **R**. In this template, **C** is the label for that construct (such as attitude), and **R** names the category of responses (such as object-evaluative judgments) assumed to be influenced by that construct.* (Greenwald & Banaji, 1995, p. 5)

A key aspect of "implicit" is therefore that it is about mental contents that are not identified by the individual. Accordingly, implicit measures are usually contrasted with explicit measures such as responses in a questionnaire when participants are simply asked about their (internally accessible) evaluation of a target object. The relation between implicit and explicit measures is often unclear and empirically, their correlation tends to be weak (Dang et al., 2020). Implicit measures are most commonly based on reaction times in computer tasks that require fast categorization of stimuli (Roefs et al., 2011), a procedure that tends to lead to low levels of reliability (Dang et al., 2020; Hedge et al., 2018).

The idea of implicit processes has been used in many different ways. This has led to practical and theoretical problems, which Corneille and Hütter (2020) have outlined in great detail. In brief, implicit measures have been regarded as an indirect way of measuring attitudes (De Houwer & Moors, 2010), as measures that capture automatic processes (Gawronski & Hahn, 2019) or that relate to memory contents based on associative learning (Gawronski & Sritharan, 2010). De Houwer (2019) simply states that "implicit bias is behavior" (De Houwer, 2019, p. 1) and promotes the pragmatic view that reactions in computer tasks are behavior, which is automatically influenced by the stimuli. This fits with the somewhat provocative view that the Implicit Association Test (IAT, the most commonly used implicit measure) is a "measure without a construct" (Schimmack, 2019, p. 1).

It is important to note that the RIM does not make statements about "implicit" processes and instead postulates reflective and impulsive processes and outlines their operational principles. Accordingly, its authors categorize explicit and implicit measures according to the "cognitive operations they capture" (2004, p. 239) and as a consequence, a good measure of impulsive processes should tap into the associative structure of the impulsive system while minimizing conscious control (Hofmann, Friese, & Strack, 2009). How well these criteria are met differs between the precise task for measurement and is subject to much discussion (De Houwer & Moors, 2010; Gawronski & De Houwer, 2014; Gawronski & Hahn, 2019; Hahn & Gawronski, 2017; Keren & Schul, 2009).

Regarding the automaticity of processes, the RIM assumes that processes in the impulsive system work efficiently and independently of intentions, two key features of automaticity (Bargh, 1994; Bargh et al., 2012; Strack & Deutsch, 2004). However, impulsive processes in the RIM are not strictly automatic in Bargh's (1994) sense as they do not necessarily happen outside of conscious awareness.

2.6 INTERVENTIONS DERIVED FROM DUAL-PROCESS MODELS

Despite the criticism they have attracted, it is undisputed that dual-process models have sparked not only much descriptive research into impulsive processes involved in health behaviors (which will be outlined further in the section "Literature Review"; see also Sheeran et al., 2016) but also different lines of interventions that take these processes into account and/or aim to change them. Hollands and colleagues (Hollands et al., 2016) present a framework to describe how conscious and non-conscious processes can work in behavior change interventions. The two main contributions of this framework are (1) the insight that the potential for conscious awareness is gradual rather than dichotomous, and (2) differentiating which part(s) of an intervention are consciously accessible: the initiating stimulus, the resulting behavior, and/or the causal link between them. Marteau, Hollands, and Fletcher (2012) describe the importance of targeting automatic processes and differentiate two major ways to do this: altering environments and targeting associative processes.

Altering environments involves methods such as re-arranging food in a canteen in a way that supports the choice of healthy options without removing unhealthy options, for example by placing healthy objects closer to customers (Rozin et al., 2011). These interventions are considered to target automatic processes since they do not require individuals in the target population to use cognitive effort to deliberately consider the healthier option. While this literature around "nudging" has received a considerable amount of attention (e.g. Arno & Thomas, 2016; Hollands et al., 2017; Landais et al., 2020), it is not at the center of this thesis. Instead, this thesis is concerned with interventions targeting associative processes.

Researchers have developed a range of interventions that aim to influence behavior not via effortful reflective processes but instead to directly alter the associative structure of the impulsive system as described in the RIM. Typically, these are adapted versions of computer tasks commonly used for measurement purposes in cognitive and social psychology (for other techniques see van Beurden et al., 2016). While details differ between the tasks, the basic idea is for the participant to learn an association between stimuli and a response that is incompatible with the behavioral impulse triggered by that stimulus (Lally & Gardner, 2013). The descriptions given here are typical versions of these tasks but there is variation in the precise task setups.

Evaluative Conditioning: in evaluative conditioning, participants passively view a computer screen where they perceive two stimuli in close temporal or spatial proximity. Typically, the initially neutral or positive conditioned stimulus (e.g. an image of unhealthy food) is followed by an inherently aversive unconditioned stimulus (e.g. of something that elicits disgust). This creates an association between both stimuli such that the conditioned stimulus takes on the negative valence of the unconditioned stimulus and subsequently elicits disgust itself.

Approach-Avoidance task: an Approach-Avoidance task presents participants with images of objects (e.g. healthy and unhealthy foods) with the instruction to move a joystick or press a key associated with an approach or avoidance movement depending on a reaction cue, typically a structural feature of the image (e.g. its spatial orientation). Upon reaction, a zooming feature disambiguates the effect of the reaction, such that approached stimuli become larger and avoided stimuli smaller. In a measurement version of the task, the reaction cue and the content are unrelated, such that all content categories are approached

and avoided equally often. An approach bias is then calculated as the difference in reaction times between approaching and avoiding for different image categories. Generally, it should be easier to approach desirable and avoid undesirable objects (Eder et al., 2013; Krieglmeyer et al., 2010, 2013).
To use this task as an intervention, the reaction cue and the image category are paired systematically such that unhealthy foods predominantly require an avoidance reaction, creating an association between stimulus and reaction.

Stop-Signal task: originally designed to measure response inhibition (the ability to override an initiated response), the stop-signal task typically presents participants with images in one of two locations and the instruction to indicate their location with a key press. In a share of trials (usually 25%), participants hear an auditory stop signal that signifies that they should not react on this trial. The delay between the presentation of the image and the stop signal varies based on participants' performance and gives an estimate of the participant's response inhibition ability.
In food Stop-Signal training, stop signals always appear with images of unhealthy food to create an unhealthy-stop association.

Go/No-Go task: similar to the Approach-Avoidance task, the Go/No-Go task presents images alongside a reaction cue (such as a structural feature of the image or a separate cue like a green or red frame around the image), which indicates what participants are to do in this trial. With a Go-cue, participants press a button as fast as possible while inhibiting a response when there is a No-Go cue. The relative probability of Go and No-Go cues varies between studies with some presenting predominantly Go-trials and others 50% Go and No-Go trials, respectively. Researchers have used reaction times on Go-trials and error rates on No-Go trials as indicators of response inhibition, the ability to stop a triggered reaction. Similar to the other tasks, an intervention version of the Go/No-Go task systematically pairs images of unhealthy foods with No-Go cues, creating an association between those foods and reaction suppression.

Even though the tasks are superficially very similar they differ in a few notable ways. Firstly, unlike the other procedures, Evaluative Conditioning does not entail a behavioral response while the Approach-Avoidance task always requires a behavioral response. Secondly, Stop-Signal and Go/No-Go task both require suppressing a response but the Stop-Signal task only delivers the stop signal after the response has been initiated while the Go/No-Go task usually gives the No-Go cue together with the stimulus. Therefore, they arguably tap into different facets of response inhibition: action restraint in the Go/No-Go task and action cancellation in the Stop-Signal task (Eagle et al., 2008; Raud et al., 2020; Verbruggen & Logan, 2008a). Additionally, performance in the Go/No-Go task might be more reflective of automatic, bottom-up response inhibition whereas the Stop/Signal task has a stronger top-down component (Verbruggen & Logan, 2008a, 2008b). Arguably, the Approach-Avoidance task also requires action restraint to suppress a dominant response (approaching a positive stimulus) and replacing it with the response required by task instructions (avoiding a positive stimulus).

Figure 1 schematically illustrates the interaction between impulsive and reflective processes when a person encounters tasty yet unhealthy food and how the different interventions alter those processes. The perception of a cookie starts the spreading activation in the associative network, including concepts like "sweet", "tasty", "sugar", and evaluative components ("good", "bad"). The activation of concepts depends on the strength of the association formed between the different nodes through frequent and recent co-activation. The activated concepts are then loaded to the reflective system and if time, motivation, and cognitive resources allow, the concepts are used in syllogistic reasoning.

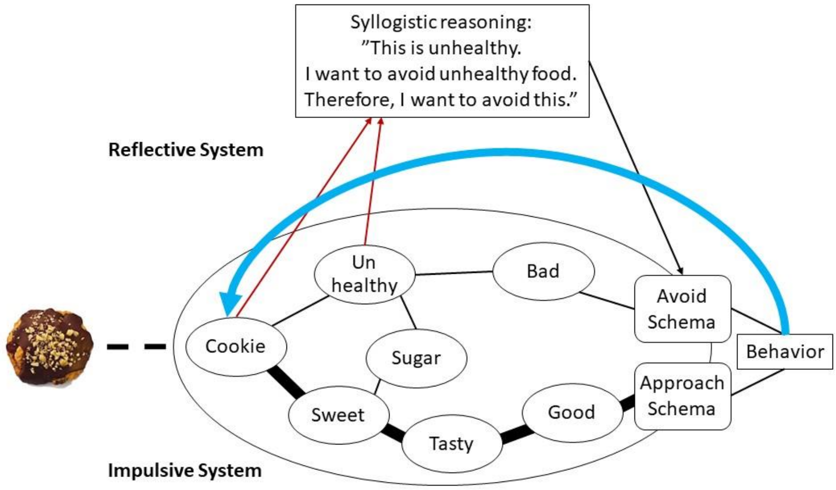

Figure 1 Theoretical framework for the study: the image in the top row shows the processes happening when encountering a food stimulus.

Figure 2 shows how Evaluative Conditioning alters the associative network by creating (or strengthening) a link between the concepts "Cookie" and "Unhealthy" or "Bad" with the end state of the associative network depicted in the right panel. Approach-Avoidance, Go/No-Go, and Stop-Signal training, on the other hand, work through the bidirectional link between behavior and the linked concepts (bottom row). By manipulating the executed behavior (inhibition or avoidance, respectively), these tasks create links between the stimulus and negative evaluations that are inherently linked to avoidance and inhibition. Additionally, they create a direct link between the stimulus and the action.

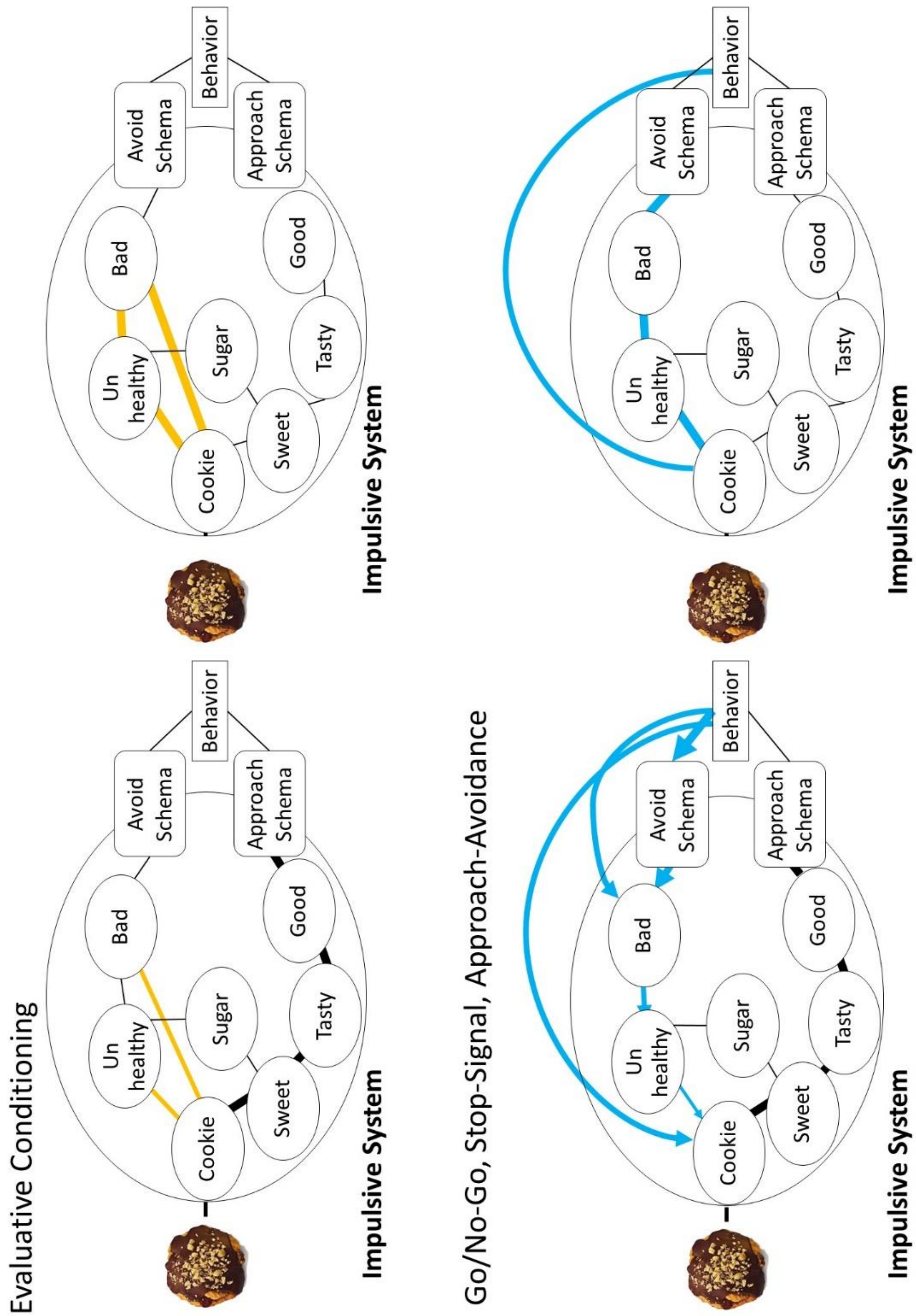

Figure 2 The top row shows how Evaluative Conditioning alters the associative network and the bottom row shows the proposed mechanism of the three behavioral tasks.

3 LITERATURE REVIEW

The following section summarizes relevant empirical findings about the role of impulsive processes in dietary behavior, including neuropsychological findings, followed by a review of the literature about interventions targeting impulsive processes.

3.1 IMPULSIVE PROCESSES IN DIETARY BEHAVIOR

Several measures of different impulsive processes have been associated with overweight and unhealthy food intake, particularly in people who are trying to restrain their food intake. A large literature is concerned with the best way to measure eating restraint and which sub-facets of the construct are most important for the development and maintenance of overweight. In brief, the Restraint Scale and the respective subscales of the Three Factor Eating Questionnaire (Stunkard & Messick, 1985) and the Dutch Eating Behaviour Questionnaire (van Strien et al., 1986) measure a person's tendency to cognitively control their food intake but mixed findings cast doubt on their usefulness to predict weight gain and overweight when not taking into account other characteristics of the person (F. Johnson et al., 2012). When referring to restraint eaters in the following, these have been identified by using any of these three questionnaires.

Restrained eaters (Alblas et al., 2019; Hollitt et al., 2010) and obese individuals (Kemps et al., 2014) show increased attention towards food stimuli in their environment. Once the stimulus is noticed and identified, network activation starts to spread in the associative system including associated evaluations and, eventually, behavioral schemata whereas positive evaluation is inherently linked to approach behavior and negative evaluations to avoidance behavior (Eder et al., 2013). Earlier studies show that restrained eaters have more positive associations with palatable and high calorie foods (Houben et al., 2010, 2012), that people with obesity have stronger associations between unhealthy food and approach behavior than normal-weight individuals (Kemps & Tiggemann, 2014), and that participants who reported susceptibility to external food cues (as measured with the Dutch Eating Behaviorar Questionnaire; Van Strien, 2002) approach food images more easily than normal eaters (Brignell et al., 2009). Further, food-approach associations are related to self-reported craving (Brockmeyer et al., 2015; Kemps et al., 2013) and generally, it is harder to stop an initiated response to food stimuli than neutral stimuli (Hofmann, Friese, & Roefs, 2009). Importantly, implicit preferences to unhealthy foods also predict more self-reported unhealthy eating behavior and higher body mass index (BMI, Fürtjes et al., 2020) and more sugar consumption, even after taking into account explicitly measured constructs such as motivation, attitudes and perceived norms (Hagger et al., 2017). Food consumption in laboratory situations is particularly high in those who show strong cognitive biases towards unhealthy foods and a low capacity to inhibit their responses towards them (Hofmann, Friese, & Roefs, 2009; Hofmann, Gschwendner, et al., 2008; Kakoschke et al., 2015). In summary, at least in some groups of people the perception of foods automatically activates positive evaluations and behavioral schemata to obtain those foods, especially when these are perceived as tasty, and these impulses are hard to control. It is thus fair to say that measures of impulsive processes are relevant to eating behavior.

Biased processing of food cues has also been demonstrated extensively on a neural level (Giuliani et al., 2018). A systematic review on the use of event-related potentials (ERPs, Carbine et al., 2018) found that ERPs associated with attention allocation (P2, P3, late positive potential) differentiate between food and non-food (e.g. Asmaro et al., 2012) and between more and less appetitive food (e.g. Becker et al., 2016).

An important ERP in this context is the N2, a negative-going deflection that peaks around 200-350 ms after presentation of the stimulus in a computer task. It is enhanced when participants need to withhold a dominant response like in a Go/No-Go task (Folstein & Van Petten, 2008) and is considered to reflect conflict monitoring (Donkers & van Boxtel, 2004) and inhibition of responses (Folstein & Van Petten, 2008; Gajewski & Falkenstein, 2013). Evidence from studies investigating the N2 have demonstrated larger amplitudes when inhibiting responses to foods generally compared to non-food images (Kong et al., 2015; Watson & Garvey, 2013) and when inhibiting responses to high- compared to low-calorie foods (Carbine et al., 2017). In this latter study, the strength of the N2 to high-calorie foods was also related to self-reported food intake. Given the N2's role as an indicator of response conflict and inhibitory control these findings support the notion that the perception of food in general and high-calorie food in particular elicits strong behavioral impulses that trigger intense conflicts when they need to be inhibited. Brain structures associated with reward processing such as the striatum, the amygdala, and the orbitofrontal cortex show stronger responsivity to high-calorie foods in obese than lean individuals (Brooks et al., 2013; Stice et al., 2010) and for high- than low-calorie foods (Mengotti et al., 2019) as do the precentral gyrus and the cerebellum, both of which are involved in attentional processes (Castellanos et al., 2009). Furthermore, the ventral medial prefrontal cortex shows weaker responses in people with higher BMI, indicating a weakened ability to inhibit food-related impulses (Batterink et al., 2010). Importantly, these biases seem to be associated with food intake (Cornier et al., 2010) and future weight gain (Stice et al., 2015).

In summary, findings from neuropsychological studies are largely in line with results obtained from reaction time tasks in demonstrating relations between biased processing of food cues and its relation to food intake and body weight. The temporal and causal relationship between increased BMI and biased processing of food cues is still unclear but is probably best described as reciprocal, with biased processing leading to weight gain, which in turn alters brain structures (Lowe et al., 2019).

3.2 ALTERING IMPULSIVE PROCESSES

Given that people generally, and people with higher BMI in particular show cognitive biases that lead them to consume more high-calorie food than is good for their health, research in recent years has examined possibilities to alter those biases with the methods described above. Some of the first promising findings on this line of interventions came from research demonstrating reductions in alcohol consumption in non-clinical (Wiers et al., 2010) and clinical samples (Wiers et al., 2011) after Approach-Avoidance training. A recent individual participant meta-analysis demonstrated small effects on cognitive biases and relapse rates with large variation between studies (Boffo et al., 2019). In the following years, researchers applied Approach-Avoidance training to food intake or snack choice in the laboratory with varying success (D. Becker et al., 2015, 2018; Kakoschke et al., 2017a; Kemps et al., 2013; Schumacher et al., 2016; Sharbanee et al., 2014). The heterogeneity in findings appears to be at least partly caused by the choice of control condition. Participants in control groups that train to approach unhealthy foods seem to increase their food intake while the participants in the active condition do not decrease their intake. When the control group receives a sham training, the effect of training seems to disappear (Kakoschke, Kemps, et al., 2018).

At the same time, other studies investigated the effects of different computer tasks and found that Stop-Signal training can improve in-lab food choice for those with low baseline inhibitory control (Houben, 2011) and that inhibiting responses to chocolate images in Go/No-Go training reduces chocolate intake in an ostensible taste test situation in people who initially liked chocolate (Houben & Jansen, 2011). Later studies showed that Stop-Signal training might only work for participants with a high level of dietary restraint (Lawrence, Verbruggen, et al., 2015), and that Go/No-Go training reduced self-selected portion size (van Koningsbruggen et al., 2014). Another study found larger effects of Go/No-Go versus Stop-Signal training on immediate food intake but cautioned that effects might be due to increased intake in the control condition (Adams et al., 2017). Go/No-Go training also reduced body weight in two studies that mainly delivered the intervention online (Lawrence, O'Sullivan, et al., 2015; Veling et al., 2014). Finally, meta-analytic findings showed significant effects on food intake and selection for the Go/No-Go but not the Stop-Signal task (Allom et al., 2016; Jones et al., 2016).

In addition to demonstrating training effects on dietary outcomes, researchers have tried to identify mechanisms of action to understand which psychological constructs are being changed by Go/No-Go training, following a more general call within health psychology to identify mechanisms of behavior change interventions (Sheeran et al., 2017). Three main accounts have received most attention in the literature: Go/No-Go training (1) strengthens inhibitory control capability, (2) creates 'automatic' associations between stimuli and inhibiting a response, or (3) leads to devaluation of food stimuli as proposed by Behavior-stimulus-interaction theory (Veling et al., 2008). In a comprehensive review, Veling and colleagues (2017) summarize research on each of these potential mechanisms and come to the conclusion that most evidence points to the devaluation of food items. Specifically, the Go/No-Go task is very easy (e.g. Veling et al., 2011), which makes it unlikely that much top-down inhibitory control is activated during task performance. At the same time and as mentioned above, the more demanding Stop-Signal task seems not to lead to desired behavioral effects (Allom et al., 2016; Jones et al., 2016). Evidence for the development of automatic response inhibition via 'food-No-Go' associations is more compelling: reactions to trained food stimuli are slower in post-training assessment or in 'catch' trials during the training (Best et al., 2016; Veling et al., 2011; Verbruggen et al., 2014), food-stop associations increase through training (Houben & Jansen, 2015), and behavioral effects seem to be stimulus-specific (Lawrence, Verbruggen, et al., 2015). The latter finding is also compatible with the third account that the value of no-go foods decreases through training. Importantly, this was only found for initially attractive foods and when participants had to actively inhibit responses, that is the effect did not occur when go trials were rare (Chen et al., 2016). The devaluation effect occurred in both student and older samples as well as with obese participants (Chen et al., 2018). Other studies found that the behavioral effect on food choice was mediated by devaluation (Veling et al., 2013) and that devaluation was related to weight loss (Lawrence, O'Sullivan, et al., 2015). Devaluation effects seem to wear off dramatically within one week and the effect of devaluation on food choice is mainly observed when participants remember Go/No-Go contingencies (Chen et al., 2020) and when time pressure during choice is high (Chen et al., 2019). This latter finding is in line with the idea that impulsive precursors of behavior are changed as participants do not have the time for effortful deliberation under time pressure. However, while some studies report more negative implicit associations after training (Kakoschke et al., 2017b), a meta-analysis found no effects on stimulus evaluation for a set of studies that mostly used an IAT to measure evaluations (Jones et al., 2016).

Importantly, the three potential mechanisms (training top-down control, food-No-Go associations, and devaluation) are not mutually exclusive: Training might initially require top-down control until food-No-Go associations are built. Following the logic of feedback loops between action and evaluation, devaluation occurs parallel to the behavioral associative link, indicating that "actions shape valuation" (Stice et al., 2017, p. 1). The question of intervention mechanisms is further complicated by the finding that conducting Go/No-Go training seems to result in a stronger attentional bias towards trained foods (Love et al., 2020), contrary to what would be expected if trained foods lose subjective value. Overall, interactions between different change processes are yet poorly understood.

Evidence for training-induced changes on the neural level is scarce. Training to inhibit responses to conditioned appetitive stimuli led to very early suppression of motor excitability (measured with motor evoked potentials), indicating that the trained stimuli triggered a weaker response tendency (Freeman et al., 2015). One study that delivered a range of cognitive training task interventions found a reduction in brain regions associated with reward processing and attention identified with fMRI (Stice et al., 2017), which was interpreted as a reduction in the rewarding value of trained foods. Another study showed increases of the P3 ERP after two weeks of intensive use of a modified version of Go/No-Go training, a result which the authors interpreted as an improvement in inhibitory control abilities (Blackburne et al., 2016). However, the version of the Go/No-Go task used in this study did not produce changes in the N2 ERP.

3.3 EHEALTH, MHEALTH AND GAMIFICATION

If interventions are to produce a sizable impact on a population scale, it needs to reach a large target population. The major avenue for such mass dissemination is online. Digital intervention delivery ('eHealth') has generally been rising and is considered to have enormous potential for behavior change for a wide range of target behaviors (Milne-Ives et al., 2020; Murray et al., 2016) including dietary behavior (Harris et al., 2011; Villinger et al., 2019). One main advantage is the potentially high efficiency since interventions can be delivered with no or little added burden to practitioners.

Computerized impulsive process interventions can naturally be implemented and disseminated to target groups easily over the internet. Indeed, several studies have demonstrated effects of such online interventions, usually including at least one face-to-face session for baseline data collection and task instructions (Forman et al., 2019; Lawrence et al., 2018; Lawrence, O'Sullivan, et al., 2015; Poppelaars et al., 2018; Veling et al., 2014). In a next step, these interventions can be delivered via mobile devices such as smartphones or tablet computers ('mHealth'), which are more convenient to use (Kakoschke, Hawker, et al., 2018; Lawrence et al., n.d., 2018; Meule et al., 2019; Milne-Ives et al., 2020; Pinder et al., 2015; van Beurden, 2018). Given smartphone penetration rates of 60-80% in industrialized countries (Poushter, 2016), the potential reach is enormous. Further advantages of mobile apps include the ease of data collection and the option to deliver just-in-time interventions that are tailored to individual participants (Nahum-Shani et al., 2018).

One main concern in eHealth and mHealth is the lack of engagement with apps and programs and the resulting fast and massive drop in intervention use (Eysenbach, 2005; Perro, 2016; Perski et al., 2017). One suggested way to keep user engagement high is the use of 'gamification', that is the inclusion of game features in an intervention that aim to make the task more fun (Forman et al., 2018; Granic et al., 2014; Johnson-Glenberg et al., 2014). Interventions that use a narrative context, feedback, progress and challenges seem to be effective for health behavior change but with variability across interventions (D. Johnson et al., 2016; Yue Chow et al., 2019). While gamification thus sounds promising and worthwhile, one study that compared a gamified and a non-gamified version of Go/No-Go training found a slightly smaller training effect on weight loss for the gamified version and excellent compliance with usage instructions regardless of gamification (Forman et al., 2019) and another study found no significant effect of a gamified Go/No-Go training relative to providing a diet-related information brochure (Poppelaars et al., 2018). Thus, it seems that gamification might not increase user engagement while potentially reducing training effects, but overall results are mixed and the field is still developing (Forman et al., 2018; Verbeken et al., 2013; Vermeir et al., 2020). That being said, the degree and kind of gamification should be considered when designing interventions.

3.4 ETHICAL CONSIDERATIONS

Altering participants' impulsive processes in a way that they might not be fully aware of raises ethical concerns as it is considered "manipulative". I would like to address this issue briefly in order to avoid confusion. A few related points seem important when considering these ethical concerns.

Firstly, we do not know for certain whether the effects of the interventions presented here work without any conscious awareness. According to the framework introduced by Hollands and colleagues (2016), there is certainly a part of the intervention component that participants might not be aware of, most probably the mechanism of how the intervention influences their behavior. However, they certainly are aware of the intervention itself: they conduct the training willfully and their behavior is a necessary component of it (which distinguishes this line of interventions, 'boosting', from 'nudging', Hertwig & Grüne-Yanoff, 2017, which might very well not be perceived with full awareness). No participant is therefore forced to undergo the intervention but voluntarily chooses to participate in it.

Secondly, and relatedly to the latter point, participants who choose to participate in or use this type of intervention usually have the conscious aim to change their dietary behavior but feel overpowered by their impulses so that their behavior and their own, consciously chosen long-term goal are not in line. By providing them with an intervention that users can self-enact (Knittle et al., 2020) to reduce the strength of those impulses, we can thus empower them to bridge their intention-behavior gap (Sheeran & Webb, 2016) and achieve their long-term goals (Veling & Lawrence, 2019), not manipulating them into doing something they do not want to. Obviously, motivating individuals to follow healthier diets in the first place is one major goal of many health interventions but is beyond the scope of this thesis (see e.g. Armstrong et al., 2011).

All efforts to change diets and decrease body weight in a population can be perceived as an evaluation of overweight and obesity as problematic and negative. This may contribute to the stigmatization of people with overweight, which increases stress and the risk of mental health problems (Tomiyama, 2014; Wang et al., 2004) and can lead to increased unhealthy food intake and further weight gain (Major et al., 2014). Especially in contexts where eating situations are understood as self-control dilemmas, the characterization of people with overweight as lacking "willpower" is easily evoked. It is thus important to emphasize that under the presented framework, overweight is understood as a product of individuals' learning history, biological factors, and the environment (Dorfman & Wallack, 2007) and not as a personal or even moral shortcoming. Similarly, a general emphasis on slim body ideals can lead to increased development of eating disorders such as anorexia nervosa or bulimia (Grabe et al., 2008). Any intervention aiming to change dietary behavior thus should consider potential negative side effects of promoting disordered eating.

4 STUDY AIMS

As reviewed in the above section, a plethora of research has demonstrated that impulsive processes play an important role in eating behavior and that these processes can be changed by behavioral computer-based interventions. The overall aim of this thesis is to improve our understanding of such interventions aiming to alter impulsive aspects of eating behavior. To achieve this, Study I provides a meta-analytical overview of the literature. Study II aims to identify a potential neural marker of involved psychological processes using EEG, and Study III turns towards practical application and provides guidelines for use of mobile-delivered Go/No-Go training. More specifically, the research questions in the three included studies are:

Study I aims to give a meta-analytical overview over different paradigms in computer-based impulsive process interventions that had thus far been meta-analyzed separately. What are the overall effects of such interventions on eating behavior and which variables moderate these effects? Do impulsive process interventions alter implicit biases and how do these changes relate to changes in eating behavior across studies?

Study II investigates the role of the N2 event-related potential in food Go/No-Go training. Does the N2 in a Go/No-Go task differentiate between high- and low-caloric foods, how does it relate to food intake, and how does it change throughout performance of food Go/No-Go training?

Study III models dose-response relationships in mobile-based food Go/No-Go training to estimate how much training is necessary to achieve measurable changes in unhealthy food intake. In addition, I investigate how this relationship differs between food categories, how measures of associative learning in the training are associated with reductions in unhealthy food consumption and how different usage patterns relate to changes in food intake.

5 METHODS

A range of research and statistical methods was used to answer the research questions in each article. In Study I, I performed meta-analysis including meta-regression with categorical and continuous moderators as well as a bivariate meta-analysis. Publication bias was assessed with several different methods. EEG was the main method in Study II and the main analyses were regression-based techniques such as repeated measures analysis of variance. The data in Study III was obtained from mobile device users in a pragmatic open trial and analyzed with linear mixed models. All studies were pre-registered on either the PROSPERO register (Study I) or the Open Science Framework (Studies II and III) and all methods followed protocol unless stated otherwise in the articles. All statistical analyses were conducted in R software (R Core Team, 2017) with the following packages: *dplyr* (Wickham et al., 2020), *tidyr* (Wickham & Henry, 2020), *plyr* (Wickham, 2011), *ggplot2* (Wickham, 2016), *afex* (Singmann et al., 2020), *stargazer* (Hlavac, 2018), *lme4* (Bates et al., 2015, p. 4), *openxlsx* (A. Walker, 2018), *statsr* (Rundel et al., 2018), *apaTables* (Stanley, 2018), *pwr* (Champely, 2018), *trimr* (Grange, 2018), *weightr* (Coburn & Vevea, 2019), and *metafor* (Viechtbauer, 2010).

5.1 STUDY I – META-ANALYSIS OF IMPULSIVE PROCESS INTERVENTIONS IN EATING BEHAVIOR

5.1.1 INFORMATION SOURCES AND SEARCH STRATEGY

Studies using human samples, published after 1990, that had an abstract in English language were searched on electronic databases (PsycInfo, Scopus, and Medline) with relevant keywords based on earlier, related reviews (Allom et al., 2016; Jones et al., 2016). Additionally, reference sections of eligible articles and similar reviews were searched and members of the European Health Psychology Society, the European Society for Clinical Nutrition and Metabolism, the International Society of Behavioral Nutrition and Physical Activity, the International Society of Behavioral Medicine, and the European Association for the Study of Obesity were contacted for unpublished data.

5.1.2 INCLUSION AND EXCLUSION CRITERIA

In order to be included, studies had to deliver training to food-related stimuli in the experimental group of a randomized control trial, using the Go/No-Go task, the Stop-Signal task, Approach-Avoidance task and/or Evaluative Conditioning. Eligible outcome measures of eating behavior for the main analysis were amount of consumed food in an ostensible taste test, snack choice and/or food diary or questionnaire data filled out by participants. For the secondary analysis, I included studies that reported a measure of implicit bias related to food stimuli regardless of whether they included a measure of eating behavior. Studies were only included when sufficient information for computation of effect sizes was provided in the article or supplementary files or by the authors on request.

5.1.3 DATA EXTRACTION AND MODERATOR CODING

Data necessary for the computation of effect sizes (means, standard deviations) were entered to a Microsoft Excel spreadsheet and outcome measures were coded as taste test consumption behavior, snack choice, or self-report data for the main outcome and implicit bias for the secondary outcome. These implicit bias measures had to be obtained reaction time tasks, such as variations of the Implicit Association Test, the Approach-Avoidance task, or the Manikin task. For k = 4 studies, I contacted the authors for necessary data that was not available in the article or supplementary files.

When more than one intervention group was compared to one control group, each comparison between active and control was entered with the sample size of the control group divided by the number of treatment groups to which it had been compared. This allows obtaining rather independent comparisons between the groups (Higgins et al., 2011).

Information on the following moderator variables was extracted and coded where available: training task (Approach-Avoidance task/Go/No-Go task/Stop-Signal task/Evaluative Conditioning, coded according to the authors' description), total number of trials in the training, percentage of avoid/no-go/stop/aversive image trials, contingency of pairing avoid/no-go/stop/aversive trials with unhealthy food stimuli, kind of signal used to indicate the required reaction in the task, whether the training was delivered online, the kind of control group ((a) "counter-training", i.e. a reversed contingency between unhealthy food stimuli and stop/no-go/avoid trials, (b) "random training", which did not display any contingency between stimuli and required response, and (c) training unrelated to food, i.e. using food-unrelated stimuli such as stationary objects). In addition, I coded participant characteristics where reported (gender ratio, mean age, baseline body-mass index), as well as inclusion and exclusion criteria of the studies, and control variables.

5.1.4 STATISTICAL ANALYSIS

Hedges' g, a corrected standardized mean difference (Cohen, 1988; Lakens, 2013), was calculated as a measure of effect size with 95% confidence intervals and Cochrane's Q and I^2 statistics as measures of study heterogeneity. High heterogeneity indicates that studies differ significantly from one another and warrants further inspection of potential moderating variables. To incorporate the expected heterogeneity of effects due to differences in interventions and samples, the meta-analysis was based on a random-effects model (DerSimonian & Laird, 1986).

Since analyzing more than one outcome from the same set of studies can lead to suboptimal effect size estimates, I also performed a bivariate meta-analysis. This method divides the covariance between outcomes into within-and between-study covariance and thus allows the estimation of both outcomes as well as the between-study correlation (Riley, 2009; Riley, Abrams, Lambert, et al., 2007; Riley, Abrams, Sutton, et al., 2007). Since only two studies reported the within-study correlation I performed the analysis with five different values (0.1, 0.3, 0.5, 0.7, 0.9) to determine how sensitive the effect size estimates were to variations in within-study correlations.

I analyzed all moderator variables in separate mixed-effects meta-regression models with categorical variables being dummy-coded and entered as binary variables and continuous moderators being used as they were. The regression coefficient of a moderator is significant if the according Q-statistic is significantly different from zero which means that the moderator alters the effect of the intervention on the outcome. I only analyzed categorical moderators for which there were three studies on each level of the moderator to allow stable estimates.

5.1.5 PUBLICATION BIAS

When studies obtaining statistically significant results are more likely to be published than those with non-significant results, meta-analytic estimates of effect sizes are too large (Thornton & Lee, 2000). This publication bias was assessed and corrected with a variety of methods. A funnel plot depicts effects size on the x- and a measure of variation (usually the standard error) on the y-axis, resulting in a symmetrical funnel shape around the average effect in an unbiased literature. Egger's regression analysis tests this symmetry assumption and can thus indicate publication bias (Egger et al., 1997).

The Trim-and-Fill method corrects biased estimates by removing outliers and adding hypothetical studies in order to restore symmetry in the funnel plot (Duval, 2005; Duval & Tweedie, 2000). To account for weaknesses of the Trim-and-Fill method, I also used a weight-function model (Vevea & Hedges, 1995) that specifies the selection of studies under publication bias and adjusts results accordingly. Carter et al. (2018) have shown that this method is effective under most circumstances.

5.2 STUDY II – THE ROLE OF THE N2 EVENT-RELATED POTENTIAL IN FOOD GO/NO-GO TRAINING

5.2.1 PARTICIPANTS

Based on available resources, n = 50 participants were recruited into the study through social media and e-mailing lists within the University of Helsinki and Aalto University. The recruiting e-mails asked for study participants in an EEG study in return for two movie tickets and spelled out the following exclusion criteria: under 18 years of age, psychiatric or neurological disease, use of recreational drugs (explained to participants to include all drugs illegal at this point in Finland, including marijuana), being pregnant or lactating, or having any food allergies, metabolic diseases, or other special diets that severely limit their dietary choices, including veganism but not vegetarianism. The study received approval from the University of Helsinki Ethical Review Board in the Humanities and Social and Behavioural Sciences.

5.2.2 PROCEDURE

Upon sign-up, participants received instructions not to eat or drink except water two hours before arriving to the laboratory to make sure they would be at least somewhat hungry. When arriving at the laboratory, the experimenter gave an overview of the experiment, asked participants to sign the consent form while giving them time to ask questions, and reassured them that they could withdraw from the study at any time without giving any reason. The experimenter then led participants to the experimental room to apply the EEG electrodes.

Participants then answered some questions on the computer (see *Measures* section), followed by the Go/No-Go task (see separate section).

During two five-minute breaks in the Go/No-Go task, the experimenter brought a bowl of M&M's candies and a plastic cup of water to the room and told the participant to take a break and eat as much candy as they like while filling out a short questionnaire on a tablet device (the questionnaire was not related to the study). After the experimenter had removed the bowl and cup after five minutes, he started the next block of the Go/No-Go task.

After completion of the Go/No-Go task, the EEG equipment was taken off and the participant was thanked for their participation, received two movie tickets, and was told they would receive a link to an online food diary for them to fill out and send back to the experimenter within a week. The entire procedure took about two hours.

5.2.3 STIMULI AND APPARATUS

All questionnaires and the Go/No-Go task were presented in E-Prime 3.0.3.60 (Psychology Software Tools Inc., 2016) software on a Windows 10 Pro computer with an LCD screen with 1024 x 768 pixel resolution and 60 Hz refresh rate at a distance of roughly 60 cm.

40 highly recognizable food images with medium brightness were selected from the food-pics database (Blechert et al., 2014) [1]. 20 images depicted foods with high energy density that were relatively unhealthy, such as chocolate or croissants (but not e.g. nuts) and 20 images foods of low caloric density, such as cucumber or berries. Distractor images of non-food objects (such as furniture or flowers) were chosen based on superficial similarity to the food images in brightness. For each participant, the software sampled seven random images of each category for use in the Go/No-Go task.

5.2.4 GO/NO-GO TASK

Each trial of the Go/No-Go task started with a fixation cross (1000ms) on a white background in the center of the screen for participants to focus their attention on, followed by the concurrent appearance of a food image (resolution of 640x480 pixels) replacing the fixation cross with a full or interrupted circle line (17 cm diameter) around it. The circles functioned as Go/No-Go cues with their meaning counterbalanced across participants. This counterbalancing as well as not using colored circles avoids potential confounding EEG patterns related to the perception of different colors or lines. Participants were instructed to press the spacebar as fast as they could when they saw a Go-cue and to not do anything when they saw a No-Go cue. Upon reaction or after 1000ms, the food image and cue were replaced by a) the fixation cross when the response was correct, b) a frowning smiley and the message "Please don't respond" when the participant had reacted to a No-Go trial, or c) a frowning smiley and the message "Faster" when the participant had not responded in time on a Go-trial. Figure 3 shows the course of three trials.

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[1] Selected picture numbers from the food-pics database (Blechert, Meule, Busch, & Ohla, 2014) are: 7, 9, 15, 27, 84, 101, 112, 151, 155, 161, 164, 168, 177, 286, 287, 293, 296, 298, 351, 510 for high calorie foods; 197, 198, 199, 242, 243, 245, 249, 250, 253, 256, 260, 263, 267, 275, 285, 334, 364, 367, 389, 429 for low calorie foods; 1002, 1008, 1012, 1015, 1019, 1022, 1024, 1033, 1036, 1038, 1050, 1055, 1059, 1080, 1094, 1132, 1144, 1155, 1200, 1208 for distractors.

The task started with 15 practice trials to familiarize participants with the task, followed by the balanced block in which pairing of high-and low-calorie images were paired with Go- and No-Go cues equally often (84 trials for each of the four combinations high calorie Go, high calorie No-Go, low calorie Go, and low calorie No-Go). Following the balanced block began the training blocks in counterbalanced order across participants. In the high-calorie No-Go block, images of high calorie foods appeared alongside No-Go cues 140 times and alongside a Go-cue 28 times with reverse numbers for the low calorie food images. In the low-calorie No-Go block, the pairing was the other way around. In both balanced and training blocks, 28 trials showed an image of a non-food object alongside a Go- and No-Go cue, which were included to divert attention from the purpose of the study and were not analyzed.

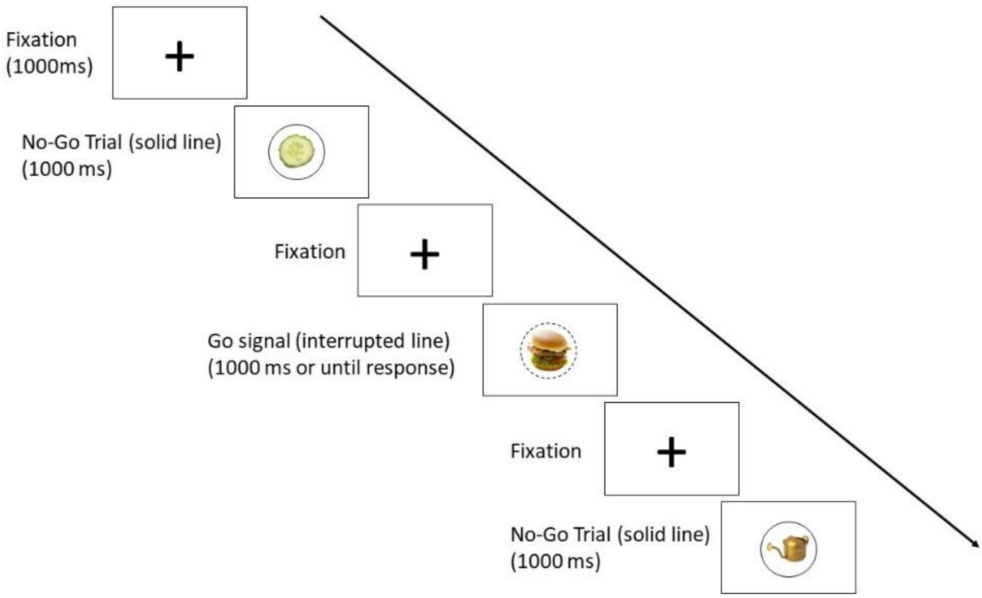

Figure 3 The course of three trials (first a low-calorie No-Go trial, second a high-calorie Go-trial, third a distractor No-Go trial). The use of full vs interrupted circles as Go- vs No-Go cues was counterbalanced between participants.

Each block was presented in four sub-blocks so participants could take a short, self-timed break and participants were instructed before each sub-block to use either their right or left hand (order counterbalanced). This was done to avoid potential confounding EEG patterns related to motor activation in either hemisphere.

The experimenter entered the room after each training block with the bowl of candies and the cup of water and participants had a break of five minutes.

5.2.5 MEASURES

Participants gave the following information before starting the Go/No-Go task: age, gender, handedness, height, weight, and how many hours ago they had last eaten, and answered six questions about satiety rated on a 7-point Likert scale ("How hungry are you right now? How full are you right now? How strong is your desire to eat right now? How much could you eat right now? How strong is your urge to eat right now? How much are you thinking about food right now?") based on Carbine et al. (2017). In addition, they provided evaluations of the 40 food items used in the study on a seven-point Likert scale.

Additionally, the following variables were recorded during and after the experiment:

Behavioral task measures: During the Go/No-Go task, reaction times on Go-trials and error to both Go- and No-Go trials were recorded.

EEG: EEG signals were measured at 2000 Hz sample rate using 32 Ag/AgCl electrodes connected to a QuickAmp (BrainProducts GmbH, Gilching, Germany) amplifier. The electrodes were positioned at equidistant sites over FP1, FP2, F7, F3, Fz, F4, F8, FT9, FC5, FC1, FC2, FC6, FT10, T7, C4, Cz, C4, T8, TP9, CP5, CP1, CP2, CP6, TP10, P7, P3, Pz, P4, P8, O1, Oz, O2 and AFz (functioned as the ground) using an elastic EEG cap (EasyCap, GmbH, Herrsching, Germany) with electrode impedance below 5 kΩ. Horizontal and vertical electro-oculographic (EOG) recordings were obtained with bipolar electrodes placed 1 cm lateral to the outer canthi of left and right eye and 1 cm above and below the left eye. The EEG and EOG signals were then down-sampled to 500 followed by application of a high-pass filter at 0.2 Hz and a low-pass filter at 80 Hz using EEGLAB software (Delorme & Makeig, 2004).

Independent component analysis was applied for artifact correction with data filtered with 1Hz high-pass and 50 Hz notch filters and segmented into wide trial-based epochs (-500 + 1200 ms). Amplitudes above 500 µV led to removal of the epoch before decomposition to reduce noise due to artifactual events. In manual screening of the components, artifactual (e.g. due to eye-movements) and clean components were identified and the EEG was reconstructed using the ICA weights on the unfiltered continuous data. The cleaned continuous data was re-referenced using average mastoid activity, followed by the application of a low-pass filter at 40 Hz and segmentation to epochs of 1000 ms locked to stimulus onset with 200 ms baseline activity. About 10% of epochs were then removed due to artifacts with larger than 35-75 µV absolute amplitude and >55-60 µV difference between the maximum and minimum amplitude. Since visual inspection of the individual ERP waveforms at fronto-central electrodes (Cz, FC1, FC2, Fz) revealed high variability in peak latency, the latency windows were defined individually for each participant. For each of the fronto-central electrodes (Cz, FC1, FC2, Fz) I calculated average amplitudes in 40 ms time windows around peak latency of participants' average N2 response. Finally, condition means were calculated for each participant.

Food intake: Food intake was measured in two ways: firstly, the candy bowls presented to the participant during the breaks in the Go/No-Go task were weighed before and after the breaks to determine the consumed amount without participants' knowledge. Each bowl contained the full contents of a bag of M&M's candies (133g). Secondly, participants filled out a retrospective 24-hour online food diary using fineli, a database containing nutritional information about the most commonly consumed foods in Finland (National Institute for Health and Welfare, 2017). They received an e-mail containing the link to the database and instructions within one week. Participants who did not fill out the diary were contacted again to keep dropout low.

5.2.6 STATISTICAL ANALYSES

A full-factorial two-way repeated measures analysis of variance (rmANOVA) tested whether N2 amplitudes in the balanced block differed significantly between high- and low-calorie and Go- and No-Go trials. The hypothesized effect should be seen as a significant interaction term between the two factors, such that high-calorie No-Go trials elicit stronger N2-amplitudes than any other condition (Hypothesis 1).

A one-sided paired samples t-test tested the effect of the training blocks on food training, with a hypothesized lower intake after the high-calorie No-Go than after the low-calorie No-Go block (Hypothesis 2).

The relation between food intake and N2 amplitudes (Hypothesis 3) was tested in a regression model, using BMI, age, gender, and hunger as control variables. The main predictor of interest was the N2-bias score. This bias score was calculated by regressing No-Go N2-amplitude scores with Go N2-amplitude scores for high and low calorie images separately and subtracting the residuals of those models one another (Meyer et al., 2017).

Lastly, the change of the N2 bias score over the course of the training (Hypothesis 4) was tested by creating N2 bias scores for the first and second half of the training blocks separately and then conducting a repeated measures ANOVA with block (high-No-Go vs low-No-Go) and part of the training (first vs second half) as factors.

5.2.7 POWER ANALYSES

Power analyses conducted with G*Power based on the feasible sample size (n = 50) and the effect size of a similar study (η_p^2 = 0.26, Carbine et al., 2017) gave .97 power to detect the interaction between calorie content and trial type in the balanced block. If assuming a smaller effect size of η_p^2 = 0.13 power would roughly be at .75.

Since no studies are available to estimate effect sizes for the other effects of interest, power analyses were based on different effect sizes. If the regression effect size were f^2 = 0.25 (a medium effect size) for predicting food intake, power was at 0.69. The t-test comparing food intake has 40% power for a small effect of d = 0.2 and 87% for an effect of d = 0.4.

5.3 STUDY III – DOSE-RESPONSE RELATIONSHIPS IN MOBILE-DELIVERED FOOD GO/NO-GO TRAINING

5.3.1 PARTICIPANTS

Participants were recruited through the FoodT mobile application downloadable from the Google Play Store [2], which was advertised to the general public through UK radio and television programs as well as social media. When starting use of the application, users could consent to use of their data for research purposes. Regardless of consent, the content of the intervention was the same for everyone.

Participants were excluded if they had a baseline BMI below 18.5 (the common threshold for underweight), were younger than 18 or older than 100 (to eliminate unrealistically high

[2] https://play.google.com/store/apps/details?id=www.psynovigo.co.uk.foodtrainersimple

age values), or if their smoking or metabolic disease status changed from baseline to follow-up.

5.3.2 PROCEDURE

Before starting use of the application, participants entered information about themselves (see section *Measures*). They then filled out a Food Frequency Questionnaire (FFQ; adapted from Churchill & Jessop, 2011; Lawrence et al., 2015) to report the frequency of consumption over the past month.

Participants then could move on to start the Go/No-Go training (described in detail in the respective section). The application recommended daily use for the first week and once weekly after that, but use was not restricted.

27 days after starting app use, the app notified participants to fill out the same questions as on first use. The app sent a reminder to participants who did not fill this questionnaire and they had up to 90 days from baseline to complete the follow-up questionnaire.

5.3.3 GO/NO-GO TRAINING

One session of Go/No-Go training consisted of three blocks of 32 trials each. The app presented 25% images of healthy foods, 25% images of unhealthy, and 50% images of non-food objects as fillers on a random location on the screen. 100ms later, a red or green circle appeared around the image as a No-Go- and Go-cue. The colors green and red were used as they are intuitively associated with going and stopping, respectively. The app also includes a setting for color-blind individuals which uses dashed and continuous lines as No-Go and Go-cues. The image and circle disappeared when tapped or after 1500ms and the interval between trials was 500ms. Healthy food images were always presented with a green circle, unhealthy images with a red circle, and neutral objects with 50% green and red. Figure 4 depicts an example of each trial type.

The app allowed users to choose up to three No-Go food categories from a range of unhealthy foods: alcohol (including beer, wine, and cocktails), biscuits, (white) bread, cake, cheese, chocolate, crisps, fast food, fizzy drinks, ice cream, (red and processed) meat, pastries, pizza, and sweets. The training then contained 8 images from each chosen category. When settings were left unchanged, FoodT presented two pictures of biscuits, one of cake, two of chocolate, and three of potato crisps in each block.

Fillers were images of clothing, flowers, and stationery that were presented category-wise in blocks and healthy food images were always three images of fruit, four of vegetables, and one of crispbread per block.

5.3.4 MEASURES

Participants reported the following information when starting app use and again 27-90 days later: age, gender, height, weight, whether they suffered from a metabolic condition, whether they were trying to lose weight, and whether they smoked. In addition, the following measures were recorded or calculated:

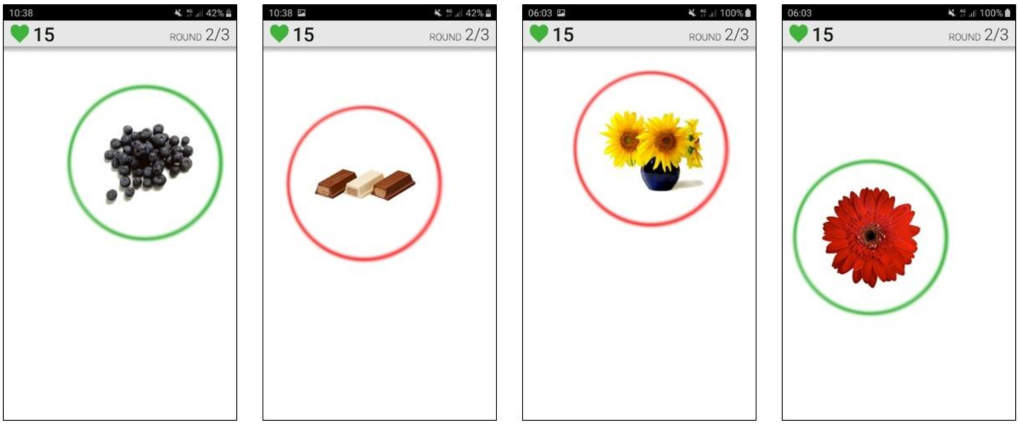

Figure 4 The four different kinds of trials as they appear in FoodT (from left to right): Healthy-Go, Unhealthy-No-Go, Filler-No-Go, Filler-Go. Green circles functioned as Go-cues, red circles as No-Go cues.

Food Frequency Questionnaire: In the Food Frequency Questionnaire participants received the instruction “Please rate how often you have eaten the following foods over the previous month.” for a set of healthy (fruit, vegetables, crispbread) and unhealthy (alcohol, biscuits, white bread, cheese, red and processed meat, pizza, cake, chocolate, crisps, fast food, fizzy drinks, sweets) foods. The app displayed images of the respective food items above the category word alongside a response bar for participants to tap. The response options were: “4 or more times a day”, “2 or 3 times a day”, “Once a day”, “5 or 6 times a week”, “2 to 4 times a week”, “Once a week”, “1 to 3 times a month”, “Less often or never”. The FFQ is a widely used instrument to assess food intake (Churchill & Jessop, 2011; Lawrence, O’Sullivan, et al., 2015; Mikkilä et al., 2015), is quick and easy to fill out, and creates relatively little participant burden.

One problem, however, is the non-linear nature of the scale: differences between response options are unequal across the scale. For example, a reduction from “2 or 3 times a day” (14-21 portions per week) to “Once a day” (7 portions per week) equals a reduction of seven to 14 portions per week, a reduction from “1 to 3 times a month” to “Less often or never” is equivalent to a change of roughly half a weekly serving. Therefore, the FFQ scores were recoded into servings per week for an exploratory analysis, in a similar procedure as used in previous studies (Mikkilä et al., 2015): “4 or more times a day” = 28, “2 or 3 times a day” = 17.5, “Once a day” = 7, “5 or 6 times a week” = 5.5, “2 to 4 times a week” = 3, “Once a week” = 1, “1 to 3 times a month” = 0.5, “Less often or never” = 0.

Conducted training: The total number of conducted training blocks was summed across the whole study period. The number of blocks for each food category was calculated by summing the number of conducted trials in each category and dividing this by eight (since each block displayed eight trials of each chosen category). Using single trials allowed taking into account training using default settings in which images of each category were not displayed eight times per block (see section *Go/No-Go training*).

Measures of associative learning: If training is successful, participants should learn the association between healthy foods and responding and between unhealthy foods and inhibiting a response. Two measures were computed to reflect this learning: a) the *error learning index* follows the logic that a participant who has learned the association between unhealthy foods and stopping should commit fewer errors on unhealthy-No-Go trials than on filler-No-Go trials since fillers were not predictive of Go or No-Go. The index therefore indicates the difference between error rates to unhealthy No-Go trials and filler No-Go trials. The b) *reaction time learning index* follows a similar logic: reactions to healthy foods should be faster than to filler images since the former are always Go-trials while the latter are not. The index is thus the difference between reaction times on filler trials and reaction times to healthy foods. In both indexes, larger values reflect better learning of the associations in the task.

Training density: The share of all training sessions that was conducted on the most active day was used as a measure of training density. This measure is large for participants who conducted most or all their training on one day and low for those who spread out training evenly over time.

Lag: This was the time interval between the last training session and filling out the FFQ a second time. Analyzing this variable allows estimating how strongly training effects wear off over time: if a longer lag is associated with less favorable outcomes, this indicates that training effects wear off and training should be conducted continuously.

5.3.5 HYPOTHESES AND STATISTICAL ANALYSES

The following hypotheses were pre-registered before accessing the data. Results from all other analyses should be regarded as exploratory.

Hypothesis 1: There is a significant positive relationship between the amount of conducted training and the reduction in unhealthy food intake and the increase in healthy food intake.

Hypothesis 2: The relationship from hypothesis 1 differs by specific food category. No specific hypotheses about effect sizes for single food categories were formulated due to a lack of previous research into this matter.

Hypothesis 3: Higher values on indexes of associative learning between food type (healthy vs unhealthy) and performing or withholding a response (Go vs No-Go) are associated with improvements in eating behavior.

All analyses in this study were based on linear random-intercept models. The outcomes were overall unhealthy food intake, healthy food intake, or intake of the specific foods for the respective research questions. The main predictor of interest in the models testing hypotheses I and II were the interaction term between the amount of training and time as a two-level factor (baseline vs follow-up) as it indicates the difference of the relationship between amount of training and intake between time points. Similarly, for the other models, the interaction between timepoint and the respective variable was the main predictor of interest. All models included age, gender, BMI, smoking status, dieting status, and metabolic condition as control variables.

6 RESULTS

6.1 STUDY I

Searches produced 7752 studies from electronic databases and 22 additional studies through other strategies. After removing duplicates, 5894 studies remained of which 502 were relevant enough to be screened by abstract. 27 of the 57 articles assessed in full text did not meet inclusion criteria, leaving 30 articles with 50 effect sizes to meta-analyze. Reasons for excluding articles were a) lack of control group (k = 8), b) no appropriate outcome (k = 4), or c) insufficient data for effect size computation (k = 1). See Figure 5 for the PRISMA flow chart.

6.1.1 MAIN RESULTS

The random-effects model resulted in a small but significant Hedges's g of -0.17, CI_{95} = [-0.29; -0.05], p = .007 across dietary outcome measures with moderate remaining heterogeneity (Q (df = 46) = 120.34, $p < .0001$ and I^2 = 61.43%), as displayed in Figure 6. The results of the model for implicit bias change were similar, g = -0.18, CI_{95} = [-0.34; -0.02], p = .02. However, the 21 studies reporting implicit bias change as an outcome showed no significant average effect on dietary outcomes (g = 0.08, CI_{95} = [-0.09; 0.24], p = .37).

The estimates from the bivariate meta-analysis ranged from g = -0.34, $p < .001$, to g = -0.37, $p < .001$ for implicit biases and from g = -0.16, $p < .001$ to g = -0.17, $p < .001$ for the dietary outcome measures, depending on the assumed within-study correlation.

6.1.2 MODERATOR ANALYSES

I conducted moderator analyses for both outcomes (consumption behavior and implicit bias) for a range of moderators, the detailed results of which can be found in the article.

The only statistically significant moderator for the dietary behavior outcome was the nature of the training task: studies using a Go/No-Go task yielded larger average effects on consumption (g = -0.39, CI_{95} = [-0.57; -0.22], $p < .001$) behavior than Approach-Avoidance task or Stop-Signal tasks (Q (4) = 13.16, p = .01). However, when conducting pairwise comparisons, the only statistically significant difference was found between Go/No-Go and Approach-Avoidance (Δg = 0.48, p = .003). See Figure 6 for a forest plot of all included effects separately for the different training tasks.

Regarding implicit biases, the assessment task for implicit biases influenced outcomes (Q (3) = 12.11, p = .007, I^2 = 50.08%) as did the kind of control group (Q (2) = 7.02, p = .03, I^2 = 49.53%). Effects were largest when implicit bias was measured with an Approach-Avoidance task (g = -0.46, CI_{95} = [-0.68; -0.25], $p < .001$) and when participants in the control group had performed a "counter-training" (g = -0.50, CI_{95} = [-0.78; -0.21], p = .001).

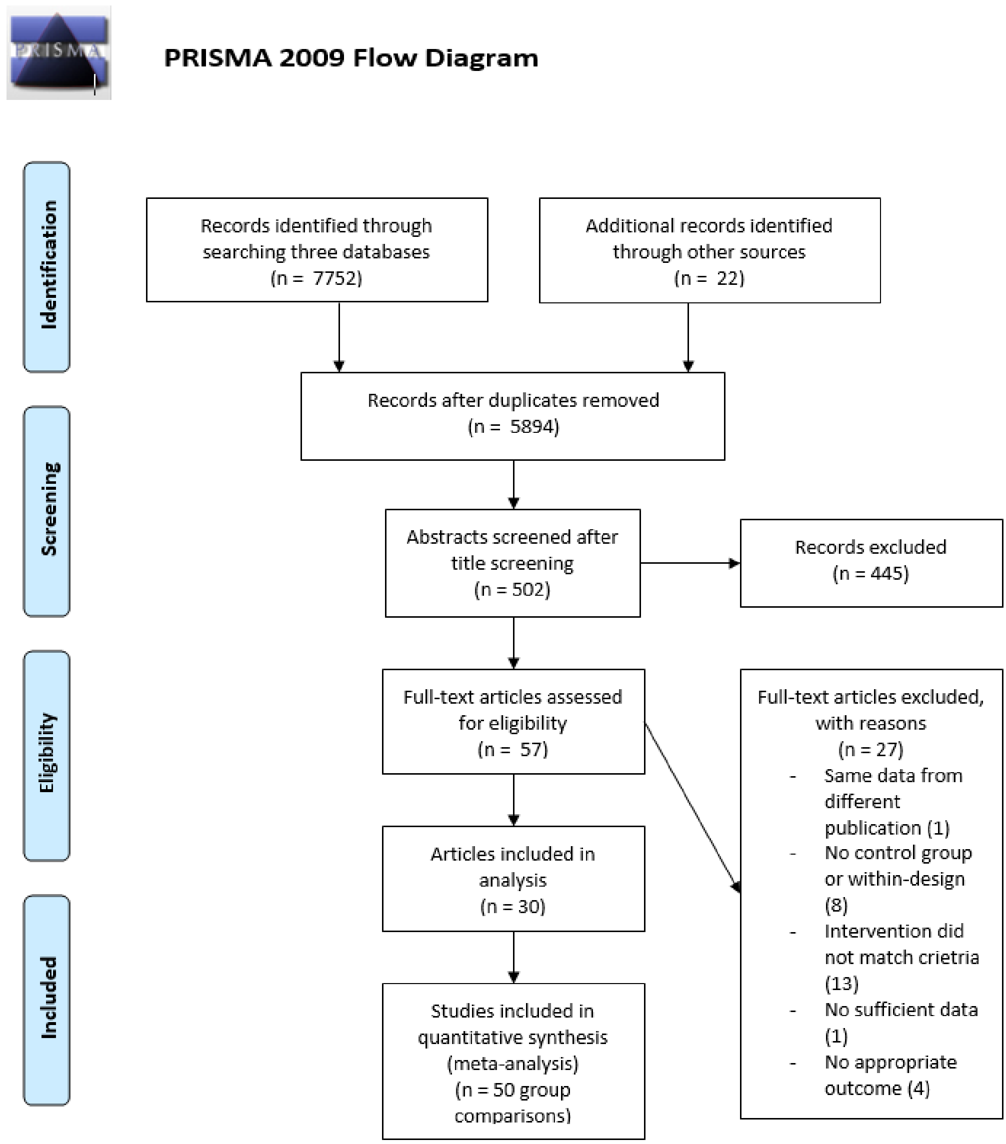

Figure 5 Flow diagram for the search and inclusion for studies in the meta-analysis (Moher, Liberati, Tetzlaff, Altman, & Group, 2009).

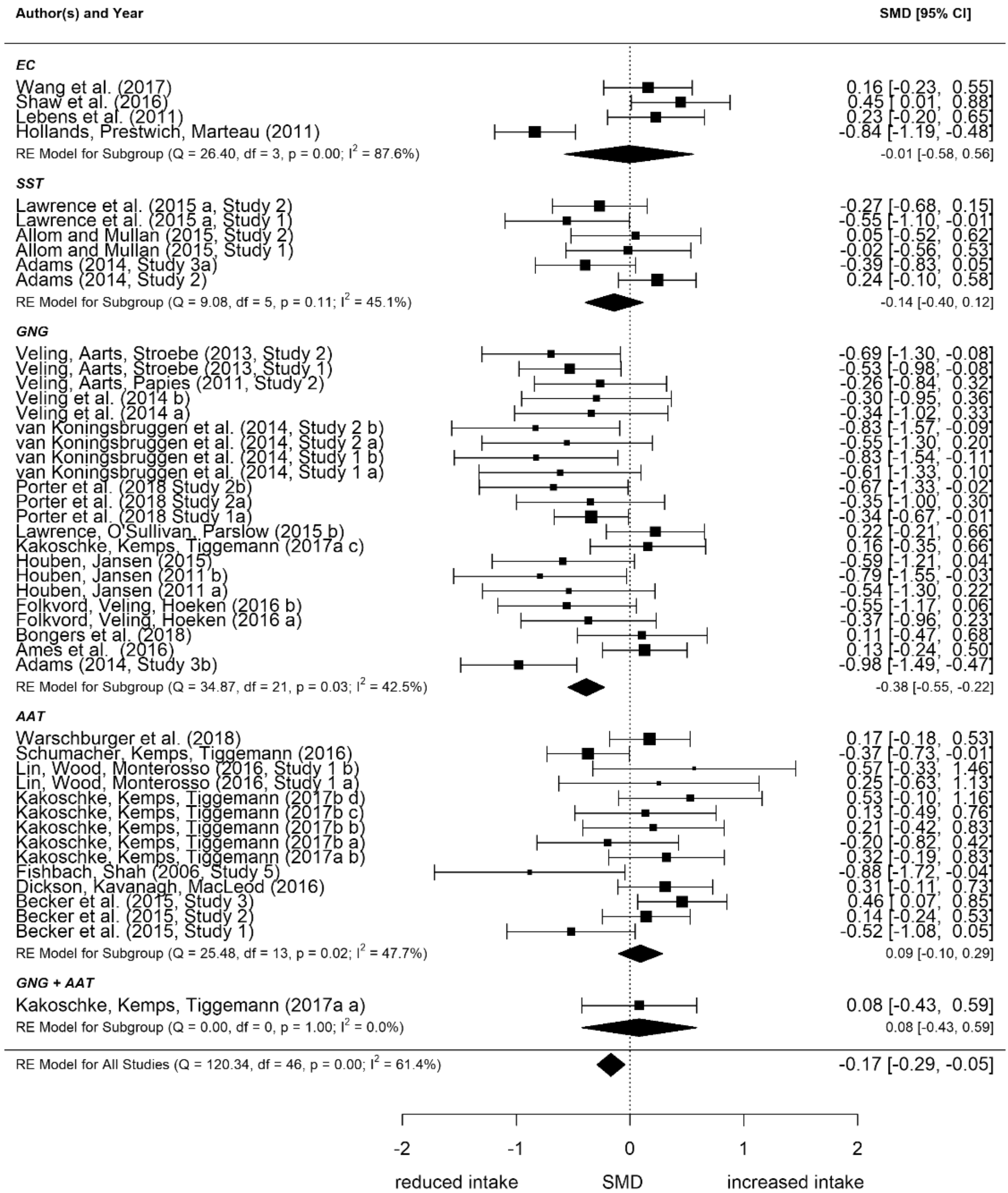

Figure 6 Forest plot for the effect sizes divided by the task used in the respective study (EC vs SST vs GNG vs AAT vs GNG+AAT).

6.1.3 RELATION OF OUTCOMES

Conducting a meta-regression predicting the effect size on dietary behavior with the effect size on implicit biases revealed a regression weight of B = .42, CI_{95} = [.02; .81], z = 2.07, p = .04, k = 21, demonstrating that the two outcomes showed a significant positive relation across studies. However, the estimate was rather uncertain as indicated by the wide confidence interval.

6.1.4 RISK OF BIAS

I constructed a funnel plot and conducted Egger's regression test to determine the amount of publication bias in the included studies. After finding a significant test indicating publication bias (z = -2.19, p = .03; Egger et al., 1997), I performed the trim and fill method, which rendered the effect non-significant (Duval, 2005; Duval & Tweedie, 2000) g = -0.02 [-0.15; 0.11], p = .79. See Figure 7 for the funnel plot including the studies "added" by the trim-and-fill method. Following the same procedure including only studies using a Go/No-Go task led to an effect size of -.25 [-.42; -.09], p = .002, a small but still significant effect.

Applying a weight function model led to no considerable changes of the effect size (g = -0.16 [-0.30; -0.01], p = .04), indicating that according to this method, no substantial publication bias was present.

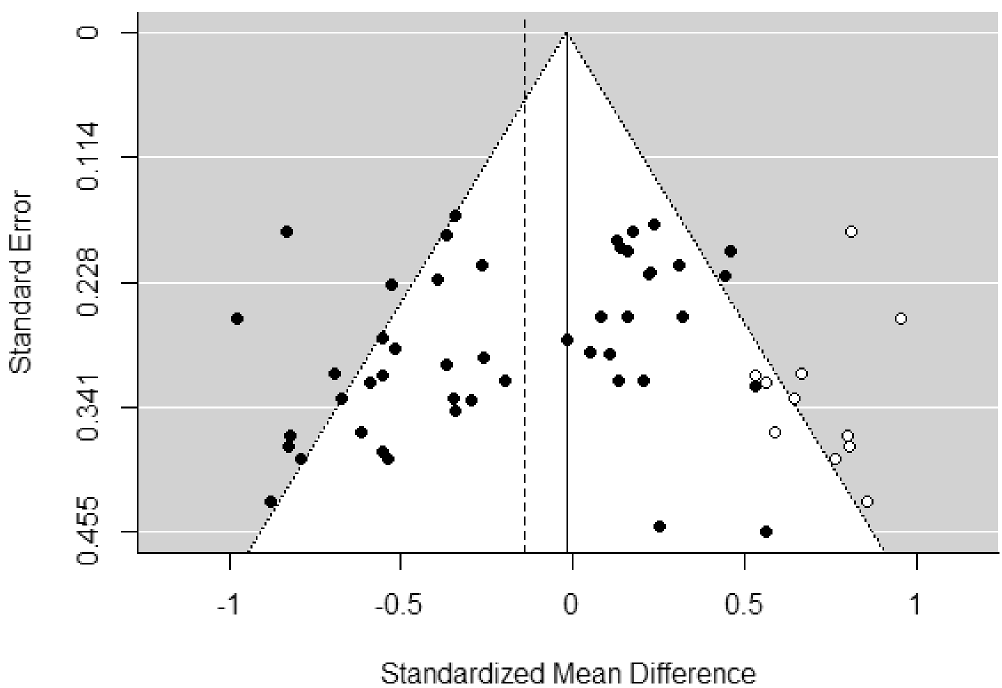

Figure 7 Funnel Plot with published studies in black and effects added by the trim and fill method in white. The dashed line indicates the estimated effect without the trim-and-fill method; the solid line indicates the estimated effect from the trim-and-fill method.

6.2 STUDY II

The 50 participants (26 female) were between 18 and 46 years old (m = 28), had a BMI between 18.5 and 30.5 (m = 23.0; 11 overweight (BMI 25 - 30) and one obese participant (BMI > 30)). Due to technical problems, data from one female participant was not usable. One participant reported unrealistic amounts of food intake in the diary and four participants did not return any food diary. These five were removed for the analyses on food intake outside the laboratory. Descriptive statistics for all participants are displayed in Table 1.

Table 1. *Descriptive statistics for the participants in Study II*

Statistic	Mean	St. Dev.	Min	Max
Age	27.92	6.48	18	46
BMI	23.01	2.60	18.51	30.45
Hours since last food intake	4.31	3.01	1	10
Hungry	3.18	1.45	1	6
Full (reverse coded)	3.39	1.63	1	6
Desire to eat	3.22	1.33	1	6
How much could eat	3.86	1.21	1	7
Urge to eat	2.96	1.32	1	7
Preoccupation with food	3.49	1.47	1	7
Average of six items	3.49	1.12	1.20	6.60

6.2.1 HYPOTHESIS 1: BASELINE N2 BIAS

The two-way repeated measures ANOVA with calorie content (high calorie vs low-calorie) and trial type (Go vs No-Go) as factors and N2 amplitude as dependent variable revealed a significant main effect of Go vs No-Go (m(No-Go)= -5.44; sd = 4.91); m(Go) = -3.60; sd= 5.11, $F(1, 48) = 19.43$, $p < .0001$, $\eta_p^2 = 0.29$), indicating that the task required activation of response inhibition on No-Go trials. Neither the main effect of calorie content (m(high-calorie food) = -4.40, sd = 5.16; m(low-calorie food) = -4.64, sd = 5.03), $p = .33$, $\eta_p^2 = 0.02$) nor the interaction effect ($p = .18$, $\eta_p^2 = 0.04$) reached statistical significance. Figure 8 displays the ERP waveforms at electrode sites Cz and Fz for all kinds of trials with the baseline block in the two left panels.

6.2.2 HYPOTHESIS 2: LABORATORY FOOD INTAKE

A one-sided dependent samples t-test evaluated whether food intake was significantly lower after the high-calorie No-Go training block than after the low-calorie No-Go block. This test was not significant ($t(48) = -1.51$, $p = .93$) and the descriptive pattern of data was against the hypothesis with food intake being higher after the high-calorie No-Go block ((m(high No-Go) = 13.33, sd = 12.57; m(low No-Go) = 11.80, sd = 11.57).

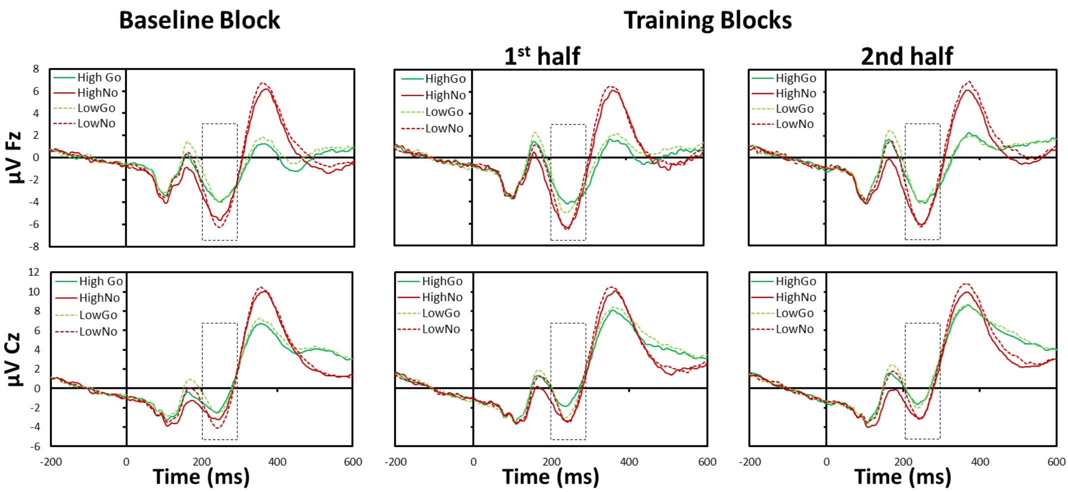

Figure 8 Grand average ERPs over Fz (top) and Cz (bottom) sites, time-locked to the onset of go/no-go cues for the baseline (left) and training (right) blocks.

6.2.3 HYPOTHESIS 3: FOOD INTAKE AND N2 BIAS SCORES

The N2 bias scores (averaged across the four fronto-central scalp sites) were not predictive of food intake in the laboratory (B = -0.41, $t(43)$ = -0.22, p = .82) or as measured with the food diary (B = 166.21, $t(38)$ = 0.63, p = .53) after controlling for BMI, age, gender, and hunger.

6.2.4 HYPOTHESIS 4: N2 AMPLITUDE CHANGE

The repeated measures ANOVA using N2 bias scores as outcome with training block (high-calorie No-Go vs low-calorie No-Go) and timepoint (first half vs second half) as factors revealed neither significant main effects nor a significant interaction (all ps > .43), indicating that the N2 did not change from the first half of the training block to the second half.

6.3 STUDY III

The 1234 participants (857 female) conducted an average of 10.7 sessions of training (range 1-122; *sd* = 10.3; *median* = 8) and reduced their mean unhealthy food intake by 0.35 points on the FFQ and their body weight by 556 grams. Additional data about the sample and their task performance is found in Table 2 and on the changes in food intake for different categories in Figure 9. The amount of training for each food category and throughout the training period can be found in *Appendix 1 and 2*.

Table 2. *Summary descriptive statistics for the sample in Study III.*

Variable	Mean/ Percent	SD	Min	Max
Age	43.03	13.98	18	92
BMI baseline	28.98	6.15	18.55	63.69
BMI follow-up	28.62	6	14.99	63.29
Weight baseline	81.82	19.05	44	159
Weight follow-up	81.29	18.54	44	160
No-Go error rate unhealthy foods	0.01	0.02	0	0.19
No-Go error rate fillers	0.02	0.03	0	0.29
Go-reaction time healthy foods	745.77	86.5	563.59	1128.92
Go-reaction time fillers	762.75	87.57	557.41	1152.01
Percent female	70.02	--	--	--
Percent dieters	46.14	--	--	--
Percent with metabolic condition	14.48	--	--	--
Percent smokers	7.66	--	--	--
Percent used personalization	50	--	--	--

6.3.1 HYPOTHESIS 1: OVERALL DOSE-RESPONSE RELATIONSHIP

Predicting unhealthy food intake in a random intercept model resulted in a regression coefficient for the interaction term of interest (time X number of training blocks) of b = -0.004, CI_{95} = [-0.006; -0.002], which indicates that conducting 252 (computed as $1/b$) blocks of training reduces unhealthy food intake by one point. The equivalent coefficient in the model predicting healthy food intake gave a point estimate of b = 0.003, CI_{95} = [0.000; 0.005].

6.3.2 HYPOTHESIS 2: DIFFERENCES BETWEEN FOOD CATEGORIES

Estimating the same parameter for all food categories resulted in regression weights ranging from 0.005 [-0.002; 0.013] for fruit to -0.059 [-0.094; -0.025] for pizza and the regression weights for cake, fizzy drinks, meat, sweets, and fruit not being significantly different from zero as indicated by confidence intervals including zero (see Table 3).

Model 2 and *Model 3* in Appendix 3 display regression weights for the sensitivity analyses outlined in the Methods section: Both predict weekly servings instead of FFQ scores and *Model 3* excludes participants with no training in this category and those responsible for floor/ceiling effects (i.e. those who indicated the lowest score for unhealthy or the highest score for healthy foods at baseline).

Table 3. *Regression weights with 95% confidence interval bounds for the timepoint by number of blocks interaction term and the number of participants included in the model. All models were controlled for age, gender, baseline BMI, presence of a metabolic condition, and diet and smoking status. The values in the columns indicating the number of sessions (i.e. three blocks) needed to change by one unit are based on the point estimate of the regression weight and are calculated as 1/regression weight. Where no value is indicated, the confidence interval of the regression weight included zero and we thus take the relationship as not significantly different from zero.*

Category	Coefficient (95CI) FFQ	n	Sessions to change by 1
ALL UNHEALTHY FOODS	-0.004 (-0.006; -0.002)	903	84.2
Alcohol	-0.022 (-0.042; -0.003)	890	15.2
Biscuits	-0.021 (-0.036; -0.005)	897	15.9
Bread	-0.023 (-0.045; -0.001)	903	14.5
Cake	-0.014 (-0.032; 0.004)	898	--
Cheese	-0.034 (-0.065; -0.003)	903	9.8
Chocolate	-0.018 (-0.031; -0.006)	902	18.5
Crisps	-0.021 (-0.04; -0.003)	403	15.9
Fast food	-0.016 (-0.032; 0)	895	20.8
Fizzy drinks	-0.041 (-0.087; 0.004)	891	--
Meat	-0.016 (-0.041; 0.008)	900	--
Pizza	-0.059 (-0.094; -0.025)	891	5.6
Sweets	-0.039 (-0.088; 0.011)	900	--
ALL HEALTHY FOODS	0.003 (0.000; 0.005)	903	129.1
Fruit	0.002 (-0.001; 0.005)	903	--
Vegetables	0.003 (0.001; 0.006)	903	111.1

6.3.3 HYPOTHESIS 3: ASSOCIATIVE LEARNING

Even though participants performed the task with very few errors overall the difference in error rates between filler-No-Go and unhealthy No-Go trials was statistically significant (t = -10.44, $p < .0001$), as was the difference in reaction times on filler-Go and healthy-Go trials (t = 4.85, $p < .0001$).

However, neither the error learning index (m = 0.009; sd = 0.02) nor the reaction time learning index (m = 17.4; sd = 19.9) significantly predicted changes in food intake of unhealthy and healthy foods, respectively (b = 1.33, CI_{95} = [-1.28; 3.95] for the error learning index and b = -0.001, CI_{95} = [-0.004; 0.002] for the reaction time learning index. This suggests that better learning of the association between healthy and Go and unhealthy and No-Go as measured with our indexes is not related to changes in healthy and unhealthy food, respectively.

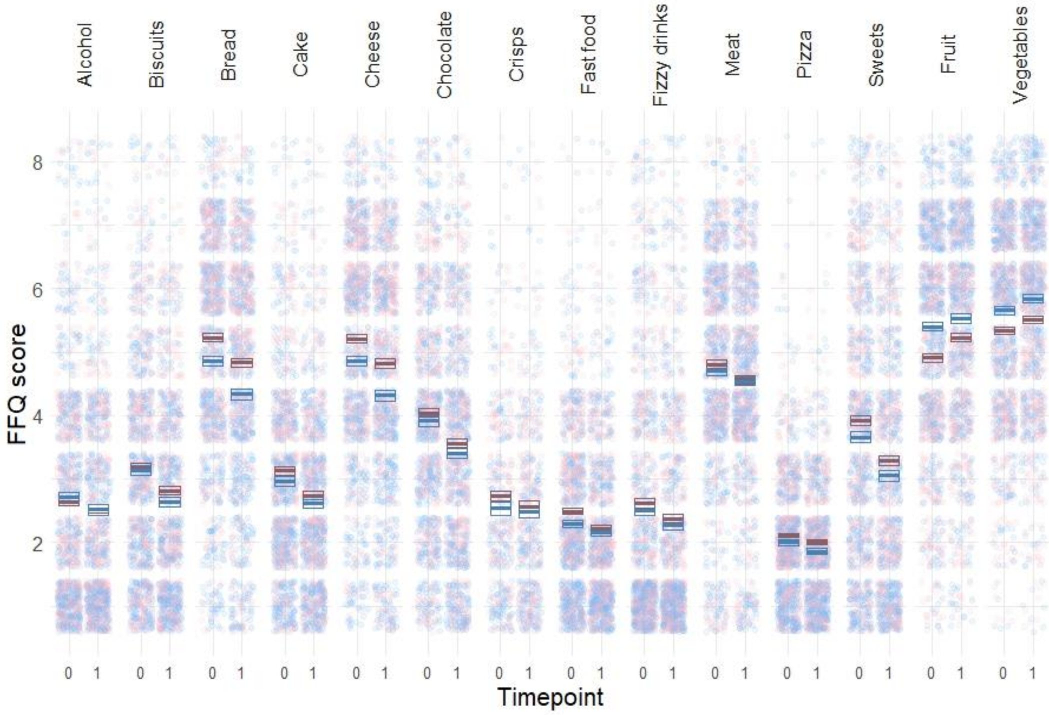

Figure 9 FFQ scores with means and standard errors by food category and timepoint. Blue dots represent dieters and pink dots non-dieters. Timepoint: 0 = baseline and 1 = follow-up.

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6.3.5 EXPLORATORY ANALYSES

I tested the effect of training density with equivalent models as used in the main analyses, resulting in a regression weight of b = 0.50, $CI95$ = [0.28; 0.71] when the number of training blocks was not included and b = 0.36, CI95 = [0.10; 0.62] when including the number of training blocks as a covariate in the same model. This indicates that concentrating training on one day reduces effects of training relative to spreading it out over the course of the training period.

Testing the time lag between the last training day and filling out the follow-up FFQ resulted in a regression weight of b = 0.012, CI_{95} = [0.008; 0.016] and b = 0.010, CI_{95} = [0.006; 0.015] when controlling for the total training amount, demonstrating that a longer lag after training is associated with less favorable outcomes.

7 DISCUSSION

7.1 OVERVIEW OF RESULTS

This thesis reports research on interventions derived from dual-process models of human cognition. The overall aim of this dissertation was to improve our understanding of computer-based impulsive process interventions involved dietary behavior by (1) summarizing the literature to estimate the effect such interventions can have on eating behavior and the impulsive processes that are involved in it, (2) examining the role of a potential neural marker of one hypothesized mechanism, the N2 event-related potential, and (3) estimating the amount of training that was necessary to achieve measurable changes in food intake when delivered via mobile devices. Table 4 summarizes the main aims and findings for each study.

Table 4. *Main aims and findings of the included studies.*

	Aims	**Main findings**
Study I	Meta-analyze RCTs on computer-based impulsive process interventions in dietary behavior	Go/No-Go training produces small significant changes in dietary outcomes Changes in dietary outcomes correlate with changes in implicit food biases across studies
Study II	Examine the role of the N2 ERP in food Go/No-Go training	N2 was not sensitive to calorie content of food images N2 amplitudes were unrelated to food intake N2 amplitudes did not change through training
Study III	Estimate dose-response relationships in mobile-based food Go/No-Go training and provide guidelines for usage	About 84 four-minute sessions over a one-month period produced a one-step change FFQ Longer time since last training session is associated with poorer outcomes

Study I found a small significant effect of computer-based impulsive process interventions on dietary outcomes such as objectively measured or self-reported food intake or food choice. Included studies delivered interventions using Evaluative Conditioning, the Approach-Avoidance task, the Stop-Signal task, or the Go/No-Go task and moderator analyses revealed that only the Go/No-Go task reduced food intake reliably. Across training tasks, interventions also reduced implicit biases towards unhealthy foods as measured with different reaction time tasks. Finally, intervention effects on dietary outcomes and measures of implicit bias were significantly correlated across studies, indicating that changes in impulsive processes are one mechanism through which these interventions work.

Study II further investigated potential mechanisms of Go/No-Go training to food stimuli and found that the N2 ERP was unaffected by the calorie content of depicted food images during a Go/No-Go task, that N2 amplitudes were unrelated to food intake, and that training to inhibit reactions to unhealthy food images did not reduce immediate food intake relative to the opposite pairing in a within-subjects design. Perhaps most notably, the N2 did not change over the course of the training, indicating that at least on this short timespan, conflict monitoring does not change due to training.

To facilitate future applications, **Study III** estimated dose-response relationships in mobile-based food Go/No-Go training and demonstrated that in a large self-selected sample, roughly ten minutes of training per day over a one-month period were necessary to produce measurable reductions in unhealthy food intake. The efficiency of training varied across food categories, but it remained unclear whether this was due to self-selection effects since participants could choose trained food categories. Results and conclusions depended on the precise analysis strategy. This leaves uncertainty about the best way to analyze data from interventions tailored by users and about the significance of the category-wise analyses. Against expectations, the measures of associative learning based on reaction times and error rates were unrelated to changes in food intake. In addition, there was evidence that training effects diminished over time indicating that users should conduct the training continuously.

7.2 THEORETICAL IMPLICATIONS

The research conducted in this thesis contributes to the ongoing theoretical debate about mechanisms involved in impulsive process interventions with a specific focus on Go/No-Go training (Chen et al., 2016; Jones et al., 2016; Veling et al., 2008, 2017). Specifically, results of the conducted studies have implications for the question whether Go/No-Go training works through (1) strengthening of response inhibition, (2) creating stimulus-stop associations, or (3) leads to the devaluation of stimuli measured directly or indirectly. The meta-analytic results from Study I are relevant to this debate as they indicate that impulsive process interventions do, in fact, alter impulsive processes and that changes in implicit biases correlate with changes in dietary outcomes across studies. While this does not mean that they also correlate within studies or even within individuals over time, it is a finding that warrants further research. A meta-analysis of studies in the smoking and alcohol addiction domain found similar albeit rather variable effects on cognitive bias change as well as relapse rates using data from individual participants (Boffo et al., 2019). This demonstration of implicit devaluation is in contrast with results from an earlier meta-analysis that had found no significant effects on food evaluations which were mostly measured with an IAT (Jones et al., 2016). The main reason for this discrepancy, however, is the fact that Study I also included studies on Approach-Avoidance training whereas Jones and colleagues' analyses had a narrower focus on Go/No-Go and Stop-Signal tasks. Indeed, the effects on implicit food biases were mainly driven by studies using the Approach-Avoidance task, both for training and measurement, thus indicating that participants can improve performance in this task yet without evidence that this translates to changes in eating behavior. Study I did not include research on attentional bias modification in which participants are trained to divert their attention away from unhealthy foods and towards healthier options (Kemps et al., 2016) which reduces unhealthy food intake to a similar degree as Go/No-Go training (Yang et al., 2019). Given the similarity between attentional bias training and the interventions included in the meta-analysis with regard to the underlying logic of re-training impulsive processes and typical task setup, including studies of attentional bias training could have provided valuable insights. However, the focus of Study I were interventions that aim to alter stimulus evaluations more directly and thus excluded attentional bias training.

Studies on Go/No-Go training rarely reported implicit bias as an outcome, which appears as a major shortcoming of the literature. As of now it is unclear whether Go/No-Go training changes impulsive processes that should be affected by the associative learning in the task (Hofmann, Friese, et al., 2008; Strack & Deutsch, 2004). Referring back to the framework by Hollands and colleagues (Hollands et al., 2016) it is currently unclear to what degree the behavioral outcome of Go/No-Go training (reductions in unhealthy food intake) comes about through mechanisms that are consciously (in-)accessible, including the question whether participants are aware that performing the training changed their eating behavior.

One reason for this lack of evidence is the often poor reliability of measures obtained with reaction time tasks (Parsons et al., 2019), such as approach bias measured with Approach-Avoidance tasks or implicit associations between concepts such as variants of the Implicit Association Test (Nosek et al., 2005). Additionally, it is often unclear what exactly these tasks measure (Brownstein et al., 2018; Kurdi et al., 2020; Schimmack, 2019) and how exactly they relate to eating behavior and BMI (Vainik et al., 2013). To understand how food Go/No-Go training influences mental processing of food stimuli, valid and reliable measures of different processes should be used. Building on earlier work on the use of this paradigm in the food domain (Fazio & Olson, 2003; Klauer & Musch, 2003; Roefs, Herman, et al., 2005; Roefs, Stapert, et al., 2005), Tzavella (2020) has demonstrated that measures from the Affective Priming paradigm are sensitive to effects of Go/No-Go training, rendering it a potential outcome measure for future studies.

These limitations of reaction time tasks notwithstanding, this study adds to the wider literature on different ways of attitude formation and change, a core topic of social psychology (De Houwer et al., 2020; Forscher et al., 2019; Gawronski & Bodenhausen, 2006; Gawronski & Sritharan, 2010; Van Dessel et al., 2018). Demonstrating that implicit evaluations of food items can be changed with a simple computer task based on association of stimuli and required reactions emphasizes the importance of impulsive processes in the formation and change of attitudes.

Study II of this thesis was designed to show how biased processing of high- vs low-calorie food cues would be represented in the strength of the N2 ERP. The fact that high-calorie foods did not elicit stronger N2 amplitudes than low-calorie foods indicates that they did not differ in the strength of the behavioral impulse they elicited. The fact that another highly-powered study had found such differences (Carbine et al., 2017) might be due to differences in the precise set-up of the Go/No-Go task: 1) participants in Carbine's study reacted to the food stimulus itself, not to a separate No-Go cue and 2) No-Go trials were more rare in the Carbine study (30%) and not equally likely as Go-trials as in Study II.

Surprisingly, no change of N2 amplitudes occurred throughout the training: if devaluation of No-Go stimuli had occurred as predicted by Behavior-Stimulus Interaction theory (Veling et al., 2008), the behavioral impulse to react to them should have become less intense. A weaker impulse, in turn, should induce a less pronounced conflict when it needs to be inhibited. Consequently, the N2 as a measure for the conflict between impulse and task demands should have decreased. Alternatively, if Go/No-Go training had strengthened response inhibition capacity, the N2 amplitude should have increased. Neither being the case, the N2 seems to be a poor indicator of these processes: if it were sensitive to learning it should have changed regardless of the presented content. Potentially, effects on the N2 develop over longer timespans that we could not observe in the immediate laboratory setting. Another study also found that repeated training of a general (i.e. not food-related) hybrid flanker Go/No-Go task led to earlier occurrence of the N2 than before the training (Schroder et al., 2019), something that was not tested in the current study. The authors interpret this earlier onset of the N2 as an increase in the speed and efficiency of the inhibitory process, which matched their obtained behavioral data. Whether this might occur in food Go/No-Go training remains to be tested. Another study demonstrated changes in theta power over frontal midlines areas and mu power over sensorimotor areas, a finding that can be interpreted as training leading to increased activation of cognitive control over reactions to target stimuli (van de Vijver et al., 2018). Future research should aim to identify which neural indicator is most sensitive to Go/No-Go training effects as this can shed more light on psychological mechanisms of action. Ideally such neural markers could be used to identify responsive individuals, for example in clinical settings. Further candidate markers include the late positive potential, the P3, and early posterior negativity (Blackburne et al., 2016; Feig et al., 2017; Marmolejo-Ramos et al., 2015).

Similarly, identifying changes induced by Go/No-Go training in neural structures through fMRI could improve our understanding of behavioral training effects as well as important processes in dietary behavior more generally. Stice and colleagues (2017) have demonstrated reduced responses in reward and attention regions to high- vs low-calorie foods after an intervention including several training tasks over four weeks. Using a task similar to Go/No-Go training (Cue-Approach training), Schonberg and colleagues report neural changes indicating altered preferences for trained foods and a decreased need for top-down inhibitory control (Schonberg, Bakkour, Hover, Mumford, & Poldrack, 2014).

Another aspect of this thesis regarding potential intervention mechanisms comes from the measures of associative learning in Study III. In this data, participants showed an overall tendency to react faster to Go-trials with healthy foods than filler Go-trials, indicating they had learned that healthy foods were always paired with Go cues. A similar pattern appeared with error rates to No-Go trials which were higher for filler than unhealthy food trials. However, neither of these indices were related to reductions in food intake, questioning the idea that associative learning is the main driver of changes in food intake. These indices were somewhat crude, however, and might not have sufficiently captured effects of associative learning. Specifically, participants learn these associations very early on (Lawrence, O'Sullivan, et al., 2015) and errors were very rare in all conditions. Reaction times on 'catch' trials during the training where participants need to respond on some unhealthy food trials, might provide a better estimate of learning unhealthy-stop associations (Best et al., 2016; Veling et al., 2011; Verbruggen et al., 2014).

The fact that more training was associated with larger changes in food intake, however, is in line with predictions from dual-process models: repeating the pairing between unhealthy food and inhibiting a response more often should strengthen the associative link more strongly. Also the demonstration that a longer lag between the last training session and the timing of the follow-up questionnaire is in line with the RIM's principle of recency that claims that associations that have been activated more recently are more likely to be activated again. In this sense, impulsive process interventions are conceptually similar to mental imagery interventions in which participants imagine a future behavior and which "may serve to activate links between stored representations of action and behavioral responses." (Conroy & Hagger, 2018, p. 669). Mental imagery techniques can improve health behaviors (Conroy & Hagger, 2018; Kemps & Tiggemann, 2015) but to what degree mental imagery and Go/No-Go training work through similar psychological mechanisms is not clear. It does seems likely that both affect the structure of the associative network including relevant behavioral schemata. Whether they might reciprocally enhance effects is an interesting future research question.

In summary, while the results of the current thesis add to the debate about potential mechanisms of computer-based impulsive process interventions, they leave many issues unresolved. While the meta-analysis in Study I is limited by the availability of data in the literature, the null findings in Study II and III are inconclusive as they might hinge on methodological limitations. These limitations notwithstanding, the studies pave the way to future research in this domain as further outlined in the section *Future directions*.

7.3 PRACTICAL IMPLICATIONS

The presented research has a range of implications for application of the described interventions. The meta-analysis in Study I identified that only the Go/No-Go task reliably changed consumption behavior, at least within a short time window. This is crucial for developers of future interventions to include the Go/No-Go task instead of similar tasks such as the Stop Signal task. The effectiveness of the Approach-Avoidance task is still a matter of debate (D. Becker et al., 2018; Kakoschke et al., 2017a) and potentially, the effect of different tasks might depend on characteristics of the target individual. It is worth mentioning, that recent analyses of studies on Go/No-Go training have indicated a substantial degree of selective reporting (Carbine & Larson, 2019) but that the evidence for its effectiveness is nevertheless strong when the most recent, pre-registered evidence is included in analyses (Veling et al., 2020).

Naturally, effective interventions to support weight loss by decreasing unhealthy food intake are most important for individuals with overweight or obesity and resulting diseases. Generally, however, preventing health problems is more desirable than treating them. An important research question is therefore how well food Go/No-Go training works for preventative purposes, that is whether it supports both reducing unhealthy food intake and mainting low intake and whether lean people profit from the training similarly to overweight and obese people. The meta-analysis in Study I did not detect a moderating effect of sample BMI across studies, but some experiments have demonstrated similar devaluation effects for lean and obese participants (e.g. Chen et al., 2018). The data from Study III, however, indicate a slightly stronger effect on unhealthy food intake for participants with higher baseline BMI, in line with earlier findings (Lawrence et al., 2019; Veling et al., 2014). Sensitivity analyses in Study II in which data from overweight participants were removed indicated no effect of weight status on the results. Due to the relatively small sample, this result should be interpreted with caution.

Other factors that might moderate intervention effectiveness include baseline impulsivity (Chen et al., 2017), eating restraint (Jones et al., 2016), such that restrained eaters benefit more from following the training, or age of the participant. For example, some evidence shows training can improve snack choice in children (Porter et al., 2018) and enhance effects of obesity treatment in children and adolescents (Kemps et al., 2020). Future studies should aim to establish for which user groups effects are most likely and should target those groups specifically.

There were not enough online studies at the time Study I was conducted to examine the role of delivery mode. With regard to potential future applications this is a highly important question. Some studies indicate that online training seems to produce significant effects on food intake but it is not clear if those are comparable to effects obtained from laboratory studies (Veling et al., 2014). Another study reports smaller effects on self-reported food intake for mobile-based than computer-based training (Lawrence et al., n.d., 2018) but the reasons for this difference are unclear. Possible hypotheses include that moving during training “undoes” the effects of inhibiting responses; that the small size of the screen and therefore the food images impairs effects; or that attention is not as focused on the mobile device as it is on a computer screen. Generally, participants probably focus their attention more to the task in laboratory studies while they might be more distracted when conducting the training online. Identifying these circumstantial moderators can help to provide user guidelines.

Two important aspects to consider in intervention design and evaluation are effectiveness, that is how large is the effect of an intervention, and efficiency, that is the ratio of effect and investment in terms of time, money, and effort. Considering effect sizes, Study I showed a standardized mean difference of 0.39 on dietary outcomes. This is similar to effects of behavioral interventions on dietary intake working through more reflective processing (Michie et al., 2009, 2018). Self-monitoring, in particular, showed comparable effect sizes in a large meta-analysis of interventions on eating behavior and physical activity (Michie et al., 2009). Another intervention that is similarly brief and simple is the formation of implementation intentions. These have been demonstrated to lead to similar changes in eating behavior as Go/No-Go training (Adriaanse et al., 2011; Carrero et al., 2019; Vilà et al., 2017). While combining implementation intentions and Go/No-Go training apparently does not lead to additive effects (van Koningsbruggen et al., 2014; Veling et al., 2014), the interaction of Go/No-Go training with other interventions remains understudied (van Beurden et al., 2019).

Regarding efficiency, one must consider the burden for both participants and the people delivering the intervention. Many effective interventions like food tracking come with their own challenges, such as poor adherence, users' problems to estimate portion sizes leading to biased estimates of food intake, and the fact that users might feel controlled when needing to track food intake (Burke et al., 2005, 2011; M. C. Carter et al., 2013; Kim et al., 2016). Mobile-delivered Go/No-Go training might be more easily framed as an intervention that empowers the individual to follow their goals (Veling & Lawrence, 2019) and might be perceived as less controlling, especially when gamified (Lumsden et al., 2016; Nurmi et al., 2020). In terms of monetary costs to society, an application like FoodT can be spread widely without additional cost, even though costs for software updates apply. Obviously, with larger spread comes better cost-effectiveness since initial developing costs are stable.

Individual-focused "booster" interventions should also be compared to "nudge" or other population-focused interventions in terms of effectiveness and efficiency to avoid unnecessary public expenses. Nudge interventions in restaurants or cafeterias seem to produce similar-sized overall effects on unhealthy eating as found in Study I (Cadario & Chandon, 2018) and taxation of unhealthy foods seems to improve diets, especially when combined with subsidies of healthy foods (Niebylski et al., 2015). While such structural interventions obviously have their place in reducing levels of obesity, some points should be considered (Veling & Lawrence, 2019; L. A. Walker et al., 2019): first, nudge interventions are bound to a specific context. If one context (e.g., the work canteen) is structured to promote healthy eating but others (the home) are not, unhealthy eating will continue in all but the 'nudge' contexts. It must be noted, however, that a recent study using alcohol Go/No-Go training shed doubt on the assumption that impulsive process interventions change behavior across contexts (Jones et al., 2019). Second, the arguments in the section *Ethical Considerations* apply in that people are manipulated by nudges without their knowledge or consent. Whether or not this is ethically justifiable also depends on the public acceptability of nudges which is generally rather high (Junghans et al., 2015; Reynolds et al., 2019; Sunstein et al., 2018). Nudge interventions also have two main advantages over booster interventions: first, they require much less effort on the part of the individual. Second, they have a lower risk of creating stigma as they do not target single individuals. Ultimately, a combination of structural and individual-focused interventions is probably most likely to reduce obesity levels while not substantially limiting individual freedom of choice.

In order to make a substantial societal impact, wide dissemination of effective interventions via smartphones seems the most feasible option. Adherence to and frequent use of eHealth interventions is crucial for behavior change (Donkin et al., 2011), so intervention providers need solid evidence to give training users the best possible advice about how much, how regularly, and for how long they should use the application. Study III provides estimates for how much mobile-based training is necessary to achieve measurable changes in food intake. Based on the results from Study III in combination with results from another study that showed improved results of spaced-out training of a similar intervention (Bakkour et al., 2018), I would recommend conducting three sessions of training per day (equaling 10 to 15 minutes in total), spread out over the course of the time period and to avoid periods of no activity. Even though the results were somewhat inconclusive regarding personalized training and differences between food categories, users should pick foods that they subjectively find hard to resist and focus their training on those. The results leave uncertainty about differences between food categories in terms of dose-relationships as results depended heavily on the precise analysis strategy and there were large differences in the available data for each category. Future trials should examine these issues by varying parameters such as personalization options experimentally, using randomized controlled trials (Chambers et al., 2019) as well as within-participants approaches such as N-of-1 trials (Kwasnicka et al., 2019). This methodology also circumvents some of the problems associated with the choice of control conditions (Adams et al., 2017; Kakoschke, Kemps, et al., 2018) since participants work as their own control.

The usage recommendation given to participants in Study III was based on an earlier trial (Lawrence, O'Sullivan, et al., 2015) and 42% of participants adhered to the 10 recommended sessions over the study period. However, app use dropped off rapidly, a common phenomenon in mobile app usage (Eysenbach, 2005; Perro, 2016). Given the crucial role of continual app use, increasing user engagement should be a key research focus (Donkin et al., 2011; Perski et al., 2017). This could be achieved by individualizing the app by adding more options for No-Go foods, including a feature to add own pictures to the selection of trainable foods. This would further increase relevance to users and might help to keep engagement high (Lawrence et al., n.d.; Schubart et al., 2011; van Beurden et al., 2019).

Another way of increasing engagement would be to make the task more challenging as it is currently very easy (as evidenced by the extremely low error rates in Study III) and therefore quickly becomes boring (van Beurden et al., 2019). This could be achieved by adding secondary tasks (such as counting the appearance of certain images, Simmons et al., 2005), adjusting task speed according to user performance, or using more complex Go/No-Go rules (Veling et al., 2011). Including other tasks (such as the Cue-Approach or a flanker task) might add variability and keep interest in the application higher (Salomon et al., 2018; Schonberg, Bakkour, Hover, Mumford, Nagar, et al., 2014; Stice et al., 2017; van Beurden, Greaves, et al., 2018). Future studies should explore the effectiveness of such measures to increase engagement with the app.

When designing and further developing web- and mobile-based interventions, researchers should include members of target groups in the development process (van Beurden, Greaves, et al., 2018; van Beurden, Simmons, et al., 2018). This increases the relevance of app features for the target population and can help to avoid elicitation of negative stereotypes about overweight and obesity (Major et al., 2012).

7.4 STRENGTHS AND LIMITATIONS

The main strength of this dissertation is the range of elaborate research methods employed to research its topic and the variety of statistical techniques for data analysis. Study I provided a comprehensive overview of the literature on impulsive process interventions using meta-analytic techniques including bivariate meta-analysis, meta-regression, as well as various methods to detect and correct for publication bias. Study II used EEG to examine neural markers of processes involved in food Go/No-Go training as well as measures of food intake inside and outside the laboratory to determine the N2's relationship with food intake. In the more practically-oriented Study III, I analyzed data obtained from mobile-delivered training with state-of-the-art statistical methods to determine dose-response relationships in food Go/No-Go training, leading to practical recommendations for future users.

Additionally, all three studies were pre-registered: Study I in the PROSPERO database for systematic reviews and meta-analyses, Study II and III on the Open Science Framework, following respective recommendations for primary and secondary data analysis. Data and analysis code are or will be available publicly. All these measures are necessary steps to increase reproducibility, replicability, and trustworthiness of psychological science by being open and transparent (Munafò et al., 2017). Specifically, pre-registration is crucial to hypothesis testing as it keeps error levels at the nominal level (Lakens, 2019; Lakens et al., 2016) while publishing data and analysis code allows other researchers to reproduce the same analysis and to use the published data for further analyses, including for power analysis for future study planning (Cohen, 1988; Lakens, 2014) and individual participant meta-analysis ('mega-analysis', Sung et al., 2014).

Specific strengths of Study I are that 1) it combines interventions that had thus far only been meta-analyzed separately despite conceptual similarities and 2) it provided evidence for effects of impulsive process interventions on implicit food biases as well as relations between implicit bias change and dietary behavior. It is obviously limited by the available literature and data: having individual data available would allow the meta-analytic examination of moderators of effectiveness such as participant age or BMI as well as potential mechanisms in a more rigorous manner than was possible here. Additionally, a rather variable set of outcomes was used in the included studies, such as food diaries, food consumption in ostensible taste tests, or snack choice as dietary outcomes and versions of the Implicit Association Test, the Approach-Avoidance task, or the Manikin task as measures of implicit biases. Systematically classifying different outcomes (in particular those measured with reaction time tasks) would avoid theoretical confusion, especially given the ongoing debate around 'implicit' measures (Corneille & Hütter, 2020; De Houwer, 2019; Gawronski & De Houwer, 2014; Gawronski & Hahn, 2019). Additionally, future research should aim to determine which measures best predict long-term outcomes such as future food intake and changes in weight. Long-term follow-up measurements of food intake in real-world settings are particularly important. While food intake in the laboratory is a valid measure to identify factors affecting food consumption (Robinson et al., 2017) it is highly artificial and therefore not an ideal indicator of real-world behavior (Best et al., 2018; Robinson et al., 2015).

Study II followed pre-registered analyses to test a range of well-specified, theory-derived hypotheses. While some of these hypotheses related to replicating earlier results with slightly different task specifics, others were new and designed to expand the knowledge base around neural mechanisms of commonly used food Go/No-Go training. Limiting factors include the fact that participants did not provide ratings of the trained foods after the training, which could have been used to detect changes in explicit food liking and to determine its relationship with the N2. Additionally, both measures of food intake were crude and should be designed better in future studies, for example by offering participants a wider range of foods to select from in the laboratory and by measuring the food diary for a longer time period than 24 hours. A funneled debriefing procedure should also be added to determine the degree to which participants were aware of the study aims, particularly with regard to food intake. Since such a debriefing procedure is missing in Study II it remains unclear to what degree participants' food intake might have been influenced by their assumptions about study aims.

The strengths of Study III include the fact that its sample is large and varied in terms of age, gender, and BMI, and that it is one of the first studies to show effects of mobile-delivered Go/No-Go training. Its results are practically applicable and thus allow more specific recommendations for future intervention users. Limitations include the fact that the sample was self-selected and the study did not contain a control group, which forbids claims of causality of the intervention. The problem of self-selection particularly applies to the analyses of the single food categories as participants chose those themselves. In addition, all measures were self-reported and the structure of the FFQ creates problems when using it as an outcome variable in regression models. Given that dietary intake is notoriously difficult to measure (Burke et al., 2005; M. C. Carter et al., 2013) the FFQ was a pragmatic choice because of its ease of use.

7.5 FUTURE DIRECTIONS

Impulsive process interventions are a relatively new line of interventions and most research into this paradigm has emerged in the past decade, obviously leaving open questions and room for further improvement. The following section outlines future research themes and questions beyond those immediately related to the studies in this thesis discussed above.

To date we know very little about the temporal dynamics of training effects. While some studies have demonstrated reductions in body weight after six months (Lawrence, O'Sullivan, et al., 2015), we lack detailed knowledge about how long effects last and how to promote long-lasting behavior change. Future research should build on studies that have shown that training to meaningful categories produces persistent devaluation (Serfas et al., 2017) and measure food intake at as many time points as possible to determine possible fluctuations.

Relatedly, very little is known about how different processes (such as attentional processes and devaluation) interact (Van Malderen et al., 2020), how they jointly influence eating behavior, and the time scale of changes in these psychological processes. For example, food Go/No-Go training seems to increase attentional bias to trained foods when measured immediately after training (Love et al., 2020) but we do not know how it develops over longer times scales. It might be that even though the attention required during the Go/No-Go task is sustained immediately after training, reduced attention allocation might follow after some delay due to the achieved devaluation effects.

In addition, earlier studies demonstrate temporal fluctuations of response inhibition (Jones et al., 2013) as well as temporal variability of food desires, cravings, and feelings of temptations (Hofmann et al., 2014; Richard et al., 2017), which predict snacking behavior (Powell et al., 2017) and heavily depend on context (Allan et al., 2019). Real-time tracking of personal reasons and motives for eating certain foods have also uncovered substantial differences between people and within people over time (Renner et al., 2012; Wahl et al., 2020). All these within-person fluctuations have largely been ignored in past studies, which typically measure variables at few time points and treat them as relatively stable. This is not satisfactory as it tells little about change processes within but rather between individuals even though psychological theories claim to apply to intra-individual processes (Johnston & Johnston, 2013).

Investigating intrapersonal processes requires ecological momentary assessment (EMA), the collection of many data points over time from each participant in real-life settings (Schembre et al., 2018; Shiffman et al., 2008). EMA for food intake has become increasingly popular and further technological developments such as automatic capturing of information from food images might further reduce participant burden (Maugeri & Barchitta, 2019). Concerns about reliability of impulsive process measures assessed via smartphone should be addressed by proper piloting but earlier studies have successfully implemented reaction time tasks in EMA research (Moore et al., 2017; Powell et al., 2017; Schmitter-Edgecombe et al., 2020).

Combining knowledge about fluctuations in food intake, eating motives, food desires and temptations, and response inhibition with knowledge about temporal dynamics of Go/No-Go training would allow individual tailoring to deliver just-in-time interventions (Hardeman et al., 2019; König & Renner, 2019; Nahum-Shani et al., 2018). These might even accommodate location data to identify "danger zones" to intervene when the user approaches a critical location (van Beurden et al., 2019; van Beurden, Greaves, et al., 2018). Only when taking into account individual user characteristics can interventions unfold their full potential (Johnston & Johnston, 2013).

Learning more about the interaction between interventions targeting reflective and impulsive processes could help to develop interventions further. In its current form Go/No-Go training supposedly works mainly through associative learning but hardly any studies have examined its interacting effect with other interventions targeting more reflective processes. While there was no evidence of mutually enhancing effects for Go/No-Go training and implementation intentions (van Koningsbruggen et al., 2014), interactions with other interventions have not been researched. Potential future applications could combine training tasks such as Go/No-Go training with other interventions targeting more reflective processes such as self-tracking, goal setting, or techniques from motivational interviewing into one application, which could make for a more engaging, satisfying, and effective intervention (Nurmi et al., 2020).

8 CONCLUDING REMARKS

This thesis has presented research into computer-based interventions that can reduce the consumption of unhealthy foods by rendering them less tempting, examining different theoretical approaches and a range of empirical methods. Specifically, repeatedly inhibiting responses to unhealthy food images on a computer or smartphone screen (Go/No-Go training) decreases unhealthy food intake significantly. These interventions are a welcome addition to the toolbox for dietary change as they directly change the desire to indulge rather than addressing reflective, resource-dependent psychological processes.

Despite the volume of research including the contributions of this thesis, much is left to learn. Most importantly, understanding the intra-individual processes of change on a behavioral, cognitive, and neural level will help to further develop interventions tailored to individual needs. This requires a coordinated effort that combines research in laboratories with studies conducted in real-life settings. Proper implementation of research and intervention tools for mobile devices is essential to make a substantial impact. Given the modest size of effects observed in most studies, future research should aim to determine how food Go/No-Go training can best be combined with other intervention techniques at both individual and societal level to produce clinically significant effects.

It is important to emphasize that efforts to reduce consumption of unhealthy foods should not be confused with a dismissal of enjoyment. Food is at the heart of many cultures, eating together is a most social act, and eating tasty food is one of the greatest pleasures in many people's lives. It is the overindulgence in unhealthy foods that creates problems for both individuals and societies. The presented research contributes one piece to potential solutions.

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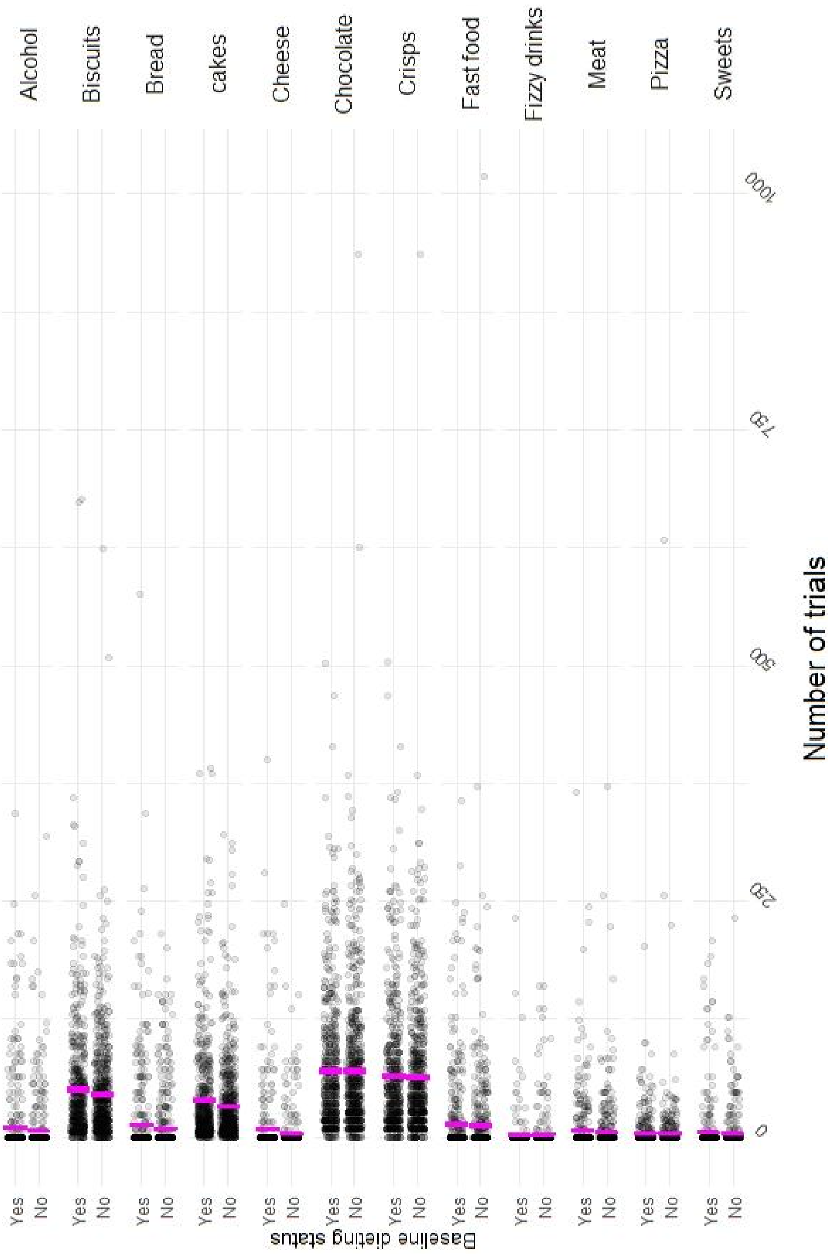
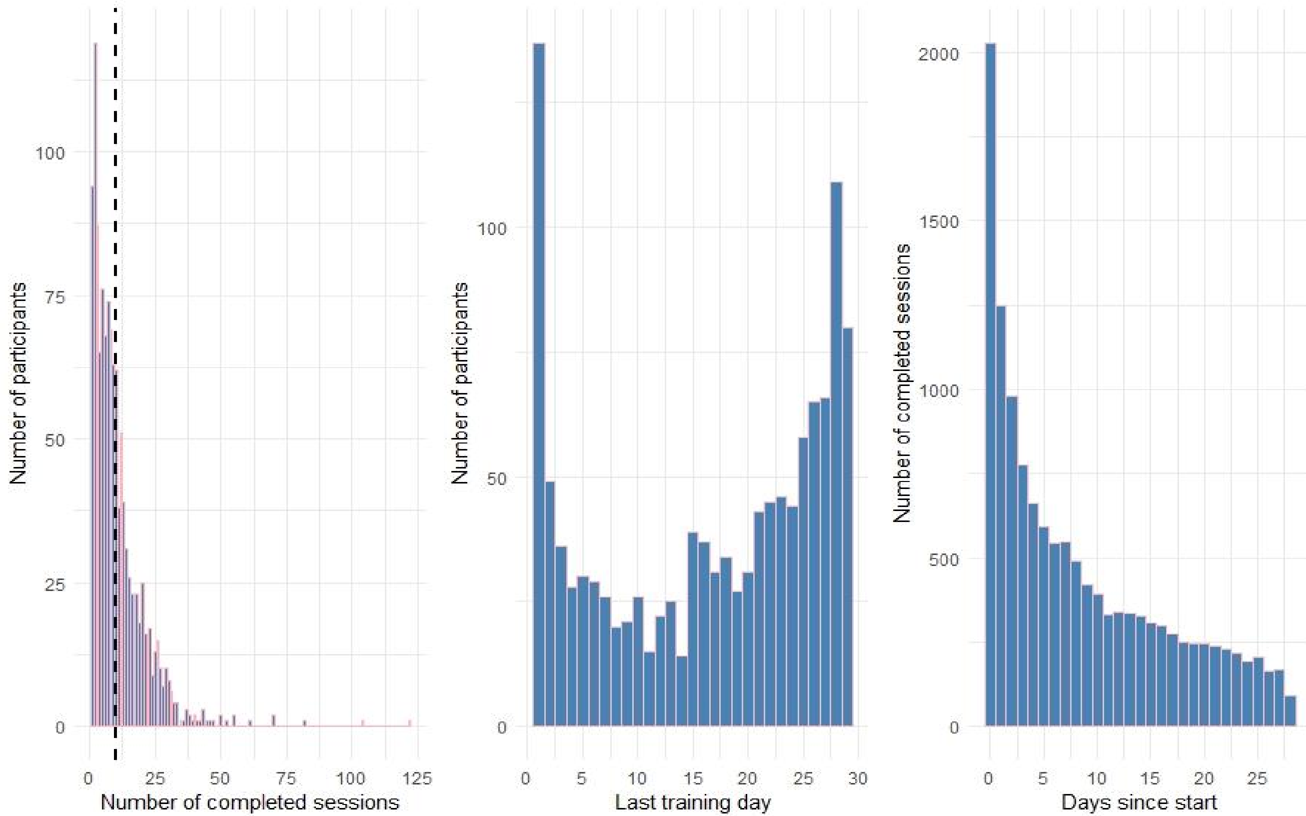
APPENDIX



(1) Number of No-Go trials conducted for each unhealthy food category in Study III. One training block included 8 unhealthy No-Go trials and one session three blocks.



(2) The left panel shows the distribution of the total amount of training sessions conducted by participants. The dashed line indicates 10 sessions which was the recommended amount of training. The middle panel shows the distribution of the last active day: many participants stopped using the app after the first day but there is another peak towards the end of the study period. The right panel shows the total number of completed sessions by day since starting use and shows a sharp decrease in the first few days.

Category	Sensitivity analyses					
	Model2 Coefficient (95CI) servings	n	Sessions to change by 1	Model3 Coefficient (95CI) subset	n	Sessions to change by 1
ALL UNHEALTHY FOODS						
Alcohol	-0.13 (-0.197; -0.063)	890	2.6	-0.066 (-0.25; 0.119)	105	--
Biscuits	-0.034 (-0.076; 0.008)	897	--	-0.025 (-0.075; 0.025)	684	--
Bread	-0.072 (-0.164; 0.019)	903	--	0 (-0.153; 0.153)	134	--
Cake	-0.018 (-0.069; 0.033)	898	--	-0.018 (-0.079; 0.042)	728	--
Cheese	-0.066 (-0.194; 0.062)	903	--	-0.05 (-0.274; 0.171)	70	6.7
Chocolate	-0.03 (-0.076; 0.017)	902	--	-0.021 (-0.072; 0.029)	807	--
Crisps	-0.009 (-0.052; 0.034)	403	--	-0.007 (-0.063; 0.05)	221	--
Fast food	-0.022 (-0.061; 0.017)	895	--	-0.039 (-0.094; 0.016)	143	--
Fizzy drinks	-0.193 (-0.341; -0.046)	891	1.7	0.021 (-0.324; 0.366)	34	--
Meat	-0.048 (-0.156; 0.059)	900	--	-0.006 (-0.133; 0.122)	113	--
Pizza	-0.07 (-0.136; -0.004)	891	4.8	-0.119 (-0.24; 0.001)	97	--
Sweets	-0.069 (-0.239; 0.102)	900	--	0.316 (-0.059; 0.687)	77	--
ALL HEALTHY FOODS						
Fruit	0.008 (-0.006; 0.022)	903	--	0.008 (-0.007; 0.022)	853	--
Vegetables	0.019 (0.005; 0.033)	903	17.5	0.024 (0.009; 0.039)	838	13.9

(3) Regression weights with 95% confidence interval bounds for the *timepoint* by *number of blocks* interaction term and the number of participants included in each model. The outcome in *Model 2* was weekly servings as re-coded from the FFQ scores using data from all participants. *Model 3* also used weekly servings as an outcome but only data from participants who (1) trained the respective food category at least once and (2) did had not indicated the minimum (for unhealthy foods) or maximum (for healthy foods) at baseline. All models were controlled for age, gender, baseline BMI, presence of a metabolic condition, and diet and smoking status. The differences in the regression weights between models result from differences in the distribution of the dependent variable (*Model 1* vs *Model 2* and *Model 3*) and in participants included in the analysis (*Model 1* and *Model 2* vs *Model 3*). The values in the columns indicating the number of *sessions* (i.e. three blocks) needed to change by one unit are based on the point estimate of the regression weight and are calculated as 1/regression weight. For those models where the confidence interval of the regression weight included zero no value is indicated, as the regression weight is not significantly different from zero.